



CALENDAR EFFECT AND RETURNS OF LISTED COMPANIES ON THE GHANA STOCK EXCHANGE: A DOLS AND GARCH MODELLING



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ABSTRACT

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This study investigated the existence of a day-of-the-week, January, and turn-of-the-month effects on the stock returns from the financial institutions and manufacturing companies listed on the Ghana Stock Exchange. Daily stock-price data, sourced from the Ghana Stock Exchange website, and accounting data for shareholder/net tangible asset value, sourced from audited financial statements of listed firms, was collected and analyzed with Fama and French's three-factor model and dynamic ordinary least square regression. In addition, a time-varying effect was examined with the generalized autoregressive conditional heteroskedasticity model. No evidence was found for day-of-the-week, January, or turn-of-the-month effects in the manufacturing sector; however, effects from day of the week and January were found to exist in the financial sector. With regard to time-varying, neither sector showed evidence of conditional volatility.

Contribution/Originality: This study is one of very few studies investigating calendar effects on African stock markets by industrial sector rather than overall stock market index. Moreover, Fama and French's three-factor model, instead of the single asset pricing model, is adopted.

1. INTRODUCTION

Several actors play a role in stock markets: market regulators, institutional and individual investors, and governments; each with their own vested interests. Investors concentrate on maximizing the returns on their own investments, which they have achieved over the years through calendar effects (Philpot & Peterson, 2011) enabling the buying and selling of stocks during periods unusually low and high returns, respectively. However, the calendar effect contradicts the efficient market hypothesis (EMH), which states that asset prices reflect all available information and ensure stocks are traded at their true value.

Fama and French (2008) believed that calendar effects did not necessarily indicate market inefficiency, though, but might result from misspecified asset pricing. Thus, they added the two factors of size and book-to-market value to the one-factor capital assets pricing model (CAPM). Similarly, Derbali and Hallara (2016) defined calendar effects as the likelihood of asset prices providing different returns at different times, which can be explained by several hypotheses: short sale, liquidity, tax-loss selling, information release, and information processing. Accordingly, the

day-of-the-week effect is the tendency for average returns to vary each day, while the January effect occurs when returns are higher in January than any other month in the year (Sarpong, 2015). Finally, the turn-of-the-month (TOM) effect arises when the daily average returns around the last day in the previous month and the first four days of the current month are significantly different from other trading days in the month (Ndungu, 2014).

Previous studies have offered various hypotheses to explain this TOM effect, of which the most notable are the payday (also known as the liquidity effect), window dressing, and information release hypotheses. Most of the previous studies on calendar effects have focused on developed markets (Gonzalez-Perez & Guerrero, 2013; Liu, 2013; Picou, 2006), paying little attention to emerging markets like Ghana (Sarpong, 2015). The current study differs in several other ways as well. First, those earlier studies that did investigate the Ghana Stock Exchange (GSE), rather than industry-level analysis, employed the GSE Composite Index (GSE-CI), an aggregate of all stocks that obscure any anomalies, which can lead to a different result. Second, studies have previously adopted a one-factor CAPM (Alagidede & Panagiotidis, 2009; Mensah, Bokpin, & Owusu-Antwi, 2016; Sarpong, 2015), which Acheampong and Agalega (2013) reported was unable to explain the stock returns on the GSE. Therefore, this study supplements the market risk factor with size and book-to-market ratio risk factors, and also applies time-varying generalized autoregressive conditional heteroskedasticity (GARCH) models to reveal the volatilities in stock returns.

2. GHANA STOCK EXCHANGE

A stock exchange in Ghana was suggested by the Commonwealth Development Finance Company Limited in its 1969 *Pearl Report*, (Mensah et al. 2016) along with the ways in which it could be established within two years. Indeed, the Stock Market Act of 1971 provided for the Accra Stock Market Limited (ASML); however, the unfavorable macroeconomic environment, political instability, and lack of government support meant the ASML was never realized. Nevertheless, over-the-counter trading of shares in some foreign-owned companies was possible through two brokerage firms: National Trust Holding Company Limited and National Stockbrokers Limited (now Merban Stockbrokers Limited) (Alagidede & Panagiotidis, 2009).

During the 1980s, Ghana underwent an International Monetary Fund (IMF)–World Bank-sponsored structural adjustment program (SAP) to correct the distortions in its economy. A range of financial reforms were undertaken simultaneously, including the deregulation of interest rates, removal of credit controls, partial relaxation of capital controls, flotation of the exchange rate, and liberalization of trade. Following financial liberalization, as well as the divestiture of non-performing state-owned enterprises, a stock exchange became essential. Recommendations from a 1989 investigation into the viability of a stock market established the GSE as a private company limited by guarantee – it later became a public company limited by guarantee in 1994. Trading eventually commenced in 1990, with 11 firms listed through 3 brokerage firms and by the end of December 2017, 42 ordinary and 1 preference shares were listed through 21 licensed stockbrokers, with a market capitalization of GH¢ 58.8 billion and profit of GH¢ 12, 368, 456.

Initially, the GSE traded just twice a week, but in 2004, it started to trade all week, excluding weekends and public holidays. Both stocks and bonds, but not derivatives, are traded either on the exchange floor, at a stockbroker's office using a wide area network, or through the internet with the GSE Automated Trading System (GATS). Although the Bank of Ghana (BoG) is the overall regulatory and supervisory authority for the whole of the financial sector, the Securities and Exchange Commission specifically regulates the GSE, which has been successful over the years. For instance, based on price indices, the GSE was ranked third among the 25 top-performing stock markets by Standard & Poor (S&P) in 2003; the GSE-CI revealed an annual return of 52.73% in 2017 compared with -15.33% in 2016; initial public offerings (IPO) on GSE have enabled businesses to access both the domestic and foreign public capital markets to fund their growth; and it has provided the means for firms to raise long-term capital. However, the uncertainty in the macroeconomic environment remains and as shown in

Figure 1, the GSE has reported nine negative annual returns since opening: 1990, 1991, 1992, 1999, 2005, 2009, 2011, 2015, and 2016.

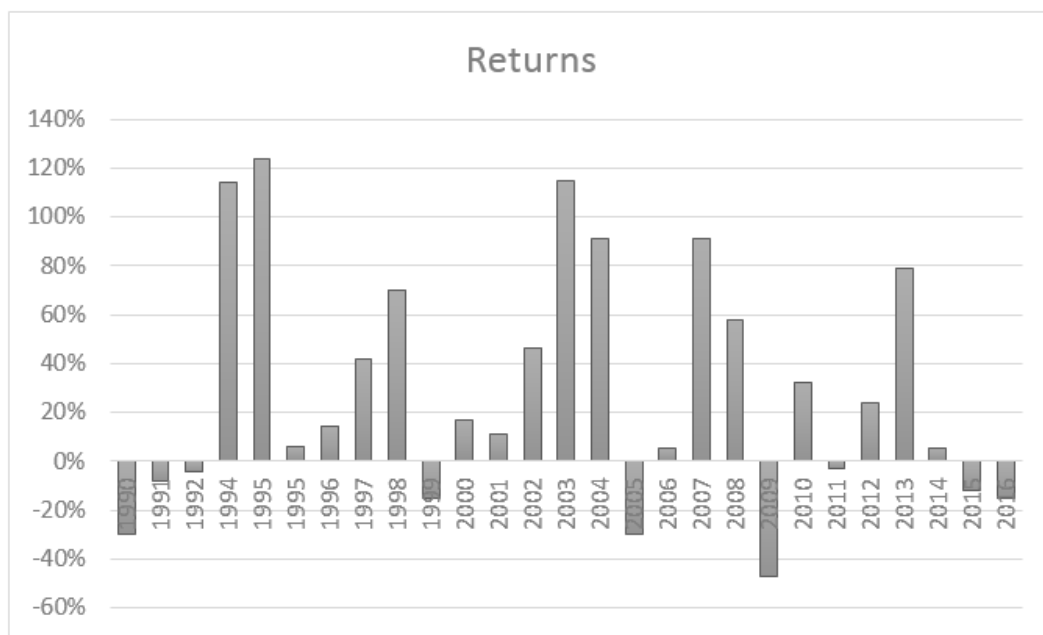


Figure-1. GSE returns (1990–2016).

Source: *eStock Analysis* (February 2017). Extracted from excel.

3. LITERATURE REVIEW

Gharaibeh and Al Azmi (2015) confirmed the day-of-the-week effect on the weighted index of the Kuwait Stock Exchange, demonstrating that the first and last trading days of the week showed a significantly positive return, whereas a negative occurred on the second. In their study of the Chittagong Stock Exchange, Islam and Sultana (2015), applying ordinary least squares (OLS) regression, GARCH (1, 1), and GARCH (1,1) with dummy variables models to determine returns and volatility, revealed significantly positive returns on Thursdays: all three models produced t-values of 4.501, 4.965, and 6.546, respectively. Furthermore, the OLS model showed significantly negative returns on Sundays, with a t-value of 2.155 and negative coefficient of 0.141.

In addition, Caporale, Gil-Alana, Plastun, and Makarenko (2016) examined whether the weekend effect could be exploited for more profits on the Ukraine Stock Exchange, using average analysis, dummy-variable regression, student's t-test, and fractional integration. Finding that returns were significantly positive on Fridays, they verified that in a long-term trading strategy, this anomaly could generate an annual profit of up to 25%. Statistically significant returns were also found for Fridays by Bundoo (2011), during an investigation into the day-of-the-week effect on the Mauritius Stock Exchange: results from the Fama and French three-factor model demonstrated that except for Fridays, the day-of-the-week effect mainly disappeared – although there was a statistically significant constant term of 5%, resulting in a 0.053% additional return, in two portfolios. In comparison, the results of the CAPM model showed statistically significant returns not only for Fridays but also Mondays, Wednesdays, and Thursdays. Evidently, the anomaly occurred regardless of the size or book-to-market value of stocks, and earlier studies would have produced different results had they used a multifactorial model.

Similar studies have been conducted for the GSE, the first of which, by Alagidede and Panagiotidis (2009), investigated both the day-of-the-week and January effects when the market traded thrice a week between 1994 and 2004. They found that the mean daily returns were 0.10% on Mondays but 0.18% and 0.19% on Wednesdays and Fridays, respectively; however, rolling-window analysis proved this to be a time-variant effect. Using more recent data, from 1990 to 2012, Mensah et al. (2016) explored whether more profitable returns were possible when investors took account of calendar anomalies. They reported the highest returns on Tuesdays and lowest on

Thursdays, a contrast that could be due more to the different models employed than a weakening effect; it is more likely that analyzing individual stocks instead of the composite index produces different results.

With regard to the January effect, Bundoo (2011) stated that it was correlated with the size effect, which had been posited in earlier studies (Blume & Stambaugh, 1983). Patel, Radadia, and Dhawan (2012) thus sought to verify this finding in both developed and emerging markets between 1999 and 2010. By applying the Mann–Whitney U and t-tests, they discovered that the size risk premium observed in January was not significantly different from the other months. Nartea, Ward, and Djajadikerta (2009) also investigated the size and January effects, as well as those of book-to-market ratio and momentum, on the New Zealand Stock Exchange. Having adapted the Fama and French three-factor model to construct a 2x3 portfolio, sorted by size and book-to-market ratio, they revealed that the size (small minus big; SMB) and book-to-market (high minus low; HML) coefficients were statistically significant, concluding that the effect was weak for size but stronger for book-to-market ratio and momentum. The January effect was not reported, however.

In Africa, John (2012) investigated the January effect on 50 stock returns listed on the Nairobi Stock Exchange (NSE) at the end of December 2011. Correlation and regression analysis found no evidence of any such effect, leading to the conclusion that no statistically significant relationship existed between January and stock returns. In contrast, Wachira (2013) did find that stock returns on the NSE were significantly different in January from other months.

Then, Sarpong (2015) examined the GSE for the January effect over two periods: first, when the 3-day trading week between 1999 and February 2, 2005; and second, the 5-day trading week between February 3, 2005 and 2014. Results from the GARCH, exponential (EGARCH), and Glosten, Jagannathan, and Runkle (GJR) models showed no evidence of the January effect during the first period, while significantly positive returns were seen for January, April, May, and June return, with significantly negative returns for March and July in the second period. Furthermore, it was recommended that future studies use the GSE all-share index (replaced by the GSE-CI in 2011) instead of the S&P Ghana Broad Market Index (BMI) index and the Databank Stock Index (DSI).

Finally, several studies have been conducted on the TOM effect. Booth, Kallunki, and Martikainen (2001, cited in Tempel, 2009) confirmed Ogden's liquidity hypothesis for the Helsinki Stock Exchange: taking the number and volume of shares traded daily, a positive relationship with TOM stock returns was found. However, McConnell and Xu (2008) rejected the hypothesis due to finding trading to be lower at the TOM compared with other days. Compton, Johnson, and Kunkel (2006) explored the US real estate sector for evidence of the TOM effect, comparing the TOM and remainder-of-the-month (ROM) stock returns by means of the OLS regression model, using ANOVA to control for monthly seasonality at the TOM. They also investigated whether returns were higher at the TOM than in the ROM for more than 50% of the months. The TOM effect was confirmed in four Real Estate Investment Trusts (REIT) indices: (50 REITs, all REITs, equity REITs, and hybrid REITs).

The TOM effect was studied in Africa by Mulumbi (2010), who concentrated on the Nairobi Stock Exchange. Following correlation and regression analysis returns were shown to be greater at the TOM compared with the ROM.

4. RESEARCH METHOD

4.1. Model

This study adopted the Fama and French (1992) three-factor model, which posits that stocks are priced according to not only their sensitivity to the market (beta) portfolio or beta but also their covariance between two hedge portfolios that reflect the return differential between both small and big capitalizations, and value and growth stocks. Thus, in theory, stock returns are affected by three factors: market (beta) sensitivity, size, and book-to-market value. This three-factor model can be expressed as the following equation (1):

$$R_{pt} - R_{ft} = \alpha_{pt} + \beta_p(R_{mt} - R_{ft}) + S_p \text{SMB}_{pt} + h_p \text{HML}_{pt} + \varepsilon_{pt} \quad (1)$$

Where:

R_{pt} is the expected return on the constructed portfolio (p)

R_{ft} is the risk-free rate of return

α_{pt} is the excess return on p

R_{mt} is the expected return of the market

$R_{mt} - R_{ft}$ is the market risk premium

β_p is the sensitivity of p to changes in the market risk premium

S_p is the sensitivity of p to changes in the size risk premium (SMB)

h_p is the sensitivity of p to s in the book-to-market value risk premium (HML)

ε is the random noise of p

The current study employed the dynamic OLS (DOLS) regression model to estimate stock return seasonality. This can be expressed in the following equation (2):

$$Rp_t = \alpha_i + \omega_{2i} N_t + \omega_{3i} E_t + \sum_{i=0}^n \pi_{1i} \Delta N_t + \sum_{i=0}^n \phi_{1i} \Delta E_t + \varepsilon_t \quad (2)$$

Where:

α_i is the Constant

ω_{2i} is the coefficient of the independent variable N_t

ω_{3i} is the coefficient of the independent variable E_t

n is the lag length

To determine day-of-the-week effects, returns must be measured for each trading day, to which dummy variables are assigned. To avoid the problem of perfect multicollinearity between the variables, only four were used, with the fifth (Friday) represented by the intercept term (the mean returns on Friday). The model for the financial sector is expressed in Equation 3.

4.2. Day-of-the-Week Effect on the Financial Sector

$$R_{pf} - R_f = E(\beta_0) + \beta_1(R_{mt} - R_{ft}) + \beta_2 \text{LSMB}_t + \beta_3 \text{HML}_t + \beta_4 D_{1t} + \beta_5 D_{2t} + \beta_6 D_{3t} + \beta_7 D_{4t} + \sum_{j=-4}^{p=4} d_1 \Delta(R_{mt} - R_{ft-j}) + \varepsilon_t \quad (3)$$

Where:

$\beta_1 \dots \dots \dots \beta_7$ are the coefficients of the variables

$D_{1t} \dots \dots \dots D_{4t}$ are the dummy variables for Monday to Thursday

Both the lag and lead time constants = 4

4.3. Day-of-the-Week Effect on the Manufacturing Sector

$$R_{pm} - R_f = E(\beta_0) + \beta_1(R_{mt} - R_{ft}) + \beta_2LSMB_t + \beta_3HML_t + \beta_4D_{1t} + \beta_5D_{2t} + \beta_6D_{3t} + \beta_7D_{4t} + \sum_{j=-4}^{p=4} d_1\Delta(R_{mt} - R_{ft-j}) + \sum_{j=-4}^{p=4} d_2\Delta HML_{t-j} + \varepsilon_t \quad (4)$$

4.4. January Effect on the Financial Sector

$$R_{pf} - R_f = E(\beta_0) + \beta_1(R_{mt} - R_{ft}) + \beta_2LSMB_t + \beta_3HML_t + \beta_4JAN_t + \sum_{j=-3}^{p=3} d_1\Delta(R_{mt} - R_{ft-j}) + \varepsilon_t \quad (5)$$

4.5. January Effect on the Manufacturing Sector

$$R_{pm} - R_f = E(\beta_0) + \beta_1(R_{mt} - R_{ft}) + \beta_2LSMB_t + \beta_3HML_t + \beta_4JAN_t + \sum_{j=-4}^{p=4} d_1\Delta(R_{mt} - R_{ft-j}) + \sum_{j=-4}^{p=4} d_2\Delta HML_{t-j} + \varepsilon_t \quad (6)$$

Where:

The coefficient estimates the January effect on returns

$\beta_1 \dots \dots \dots \beta_4$ are the coefficients of the variables

JAN_t is the dummy variable for the January effect

Both the lag and lead time constants = 4

4.6. Turn-of-the-Month Effect on the Financial Sector

$$R_{pf} - R_f = E(\beta_0) + \beta_1(R_{mt} - R_{ft}) + \beta_2LSMB_t + \beta_3HML_t + \beta_4TOM_t + \sum_{j=-5}^{p=5} d_1\Delta(R_{mt} - R_{ft-j}) + \varepsilon_t \quad (7)$$

4.7. Turn-of-the-Month Effect on the Manufacturing Sector

$$R_{pm} - R_f = E(\beta_0) + \beta_1(R_{mt} - R_{ft}) + \beta_2LSMB_t + \beta_3HML_t + \beta_4TOM_t + \sum_{j=-5}^{p=5} d_1\Delta(R_{mt} - R_{ft-j}) + \sum_{j=-5}^{p=5} d_2\Delta HML_{t-j} + \varepsilon_t \quad (8)$$

4.8. Volatility Models

This study examined volatility through a range of GARCH models—GARCH, exponential GARCH (EGARCH), and threshold GARCH (TGARCH) – allowing variances of errors to be time dependent. The EGARCH and TGARCH models have the advantage over GARCH in that they allow the asymmetric effect of good and bad news on conditional variances.

4.8.1. GARCH (1, 1)

A GARCH model comprises two equations: the mean equation is the OLS regression including the autoregressive term, while the variance equation includes a constant, ARCH, and GARCH term that account for volatility. Both equations are estimated jointly by Bollerslev and Wooldridge's (1992) quasi-maximum likelihood (QML) technique (Gbeda & Peprah, 2018). The GARCH (1, 1) mean equation is expressed as Equation 3, and the variance equation is expressed as follows:

$$h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 \quad (9)$$

Where:

h_t represents the conditional variance (i.e., the dependent variable)

ω is the constant term

β represents the conditional volatility (i.e., the GARCH effect)

h_{t-1} is the GARCH term

α represents the lagged squared error term (i.e., the ARCH effect) ε_{t-1}^2 is the ARCH term

In the variance equation, both α and β measure the market volatility: while a high coefficient value for the former indicates that volatility reacts intensely to market movements, while suggesting that persistent volatility shocks over a long period. If the sum of the ARCH and GARCH coefficients (i.e., $\alpha + \beta$) is very close to 1, volatility is highly persistent and the market may be inefficient; non-explosive volatility requires $\alpha + \beta < 1$, while h_{t-1} , ω , α , and β should be positive (i.e., ≥ 0) for non-negativity (Alagidede & Panagiotidis, 2009).

However, to assess asymmetric volatility in the stock market (i.e., the leverage effect), Zakoian's (1994) TGARCH and Nelson's (1991) EGARCH models are more appropriate.

4.8.2. TGARCH (1, 1)

TGARCH extends the GARCH model by adding the leverage effect, which refers to the tendency that bad increases volatility more than good. The mean equation remains the same (i.e., Equation 3) in TGARCH (1, 1) and the variance equation is expressed as follows:

$$h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad (10)$$

Where:

I_{t-1} is the indicator function that represents the leverage effect/asymmetric volatility.

β , α , and γ are the coefficients to be estimated.

Again, the equations are estimated jointly using the QML technique.

4.8.3. EGARCH (1, 1)

Likewise, EGARCH uses both mean, expressed in Equation 3, and variance equations, which is expressed as follows:

$$\log h_t = \omega + \beta \log h_{t-1} + \alpha \left[\left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| - \sqrt{\frac{2}{\pi}} \right] + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \quad (11)$$

Where:

ω is the Constant or intercept.

$\log h_t$, the log of the conditional variance, is the dependent variable.

β , the lagged value for the conditional variance, represents the GARCH term.

α is the coefficient of the absolute values for the difference between the standardized residual and its expected value

$$\text{(i.e., } (E(|\varepsilon_{t-1}| / \sqrt{h_{t-1}})) = \sqrt{2/\pi} \text{)}$$

$\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ is the standardized residual

As the log of the conditional variance is the dependent variable, the leverage effect is exponential rather than quadratic, which ensures that forecasts of the variance are positive even when the parameters are negative; hence, unlike GARCH (1, 1), non-negative restrictions on the variance parameters are not required. To test for leverage effects, $H_0: \gamma = 0$ γ represents asymmetric volatility: if $\gamma_1 \neq 0$, asymmetric volatility exists.

In all the GARCH models, both the mean and variance equations were estimated jointly using the QML technique as it is generally consistent, has normal limiting distribution, and provides a simple computable formula for asymptotic standard errors that are acceptable under non-normality.

4.9. Measurement of Study Variables

The current study assessed two dependent variables against four independent and three control variables. How these variables were measured is detailed in the following sections.

4.10. Portfolio Returns

The portfolio returns refer to the total average returns from all financial and manufacturing stocks in each portfolio, and are one of the dependent variables. It is measured as the weighted average returns of individual stocks within the portfolio (p) and since the study employed daily data, is expressed in days as follows:

$$R_{p,d} = \sum_{i=1}^n W_{i,d} R_{i,d} \quad (12)$$

Where:

$R_{p,d}$, represents the returns of p in day, d

n represents the number of stocks in the p, which would change at least annually

$w_{i,d}$ represents the weight of individual stocks (i) within the p

$R_{i,d}$ represents the returns of i in a d

4.11. Stock Returns

$$R_t = \log(S_t) - \log(S_t(-1)) \quad (13)$$

Where:

R_t represents stock returns

S_t represents stock prices at a certain period (t)

$S_t(-1)$ represents stock prices in the previous period

4.12. Day-of-the-Week Effect

This effect assumes that the average returns from trading on Mondays are significantly lower than on other days. It is measured using dummy variables, which is true for all calendar effects: when the observation occurs on a Monday, the dummy variable is 1; when occurring on other days, it is assigned 0.

4.13. January Effect

The January effect assumes that average returns are significantly higher in January than in other months. Again, the dummy variable is 1 when the observation occurs in January and 0 otherwise.

4.14. Turn-of-the-Month Effect

This study adopted the traditional approach of estimating the TOM effect based on four trading days: the last trading day of the month and first three trading days of the following month. The dummy variable is assigned 1 for observations occurring cumulatively on these four trading days and 0 otherwise: it is equal to 1 in the -1, +1, +2, +3 windows and 0 outside.

4.15. Size and Book-to-Market Value Effect

These are two of the control variables, as based on Fama and French’s three-factor model. The size effect is based on the median point of the market capitalization (MC) (i.e., market value of stock) for individually listed firms in each sector. Where a firm’s MC exceeds the median, it is classified as big, while those below or equal to the median are classified as small. Subsequently, the book-to-market ratios were used to determine the value effect.

First, the 70th and 30th percentiles of the average total book-to-market ratio (BE) for all stocks were calculated, against which each member of the small and big groups of firms were assessed. Firms with a BE greater than the 70th percentile are considered value stocks, while those lower or equal to the 30th percentile are considered growth stock; firms falling between the two percentiles are neutral stock.

This resulted in the construction of six portfolios, as depicted in Figure 2.

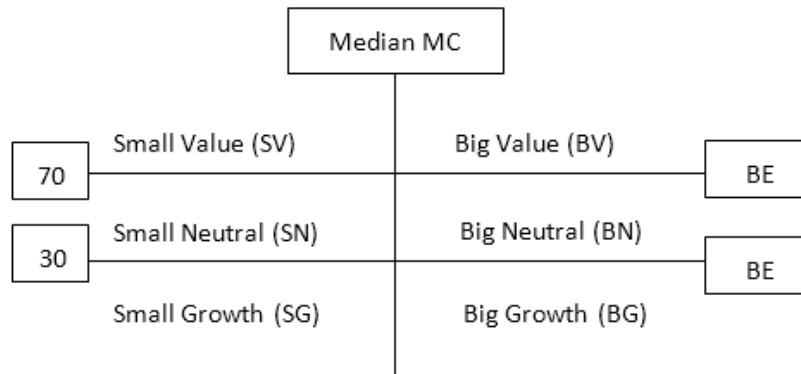


Figure-2. Six portfolios based on size and value.

In Figure 2, the firms to the left of the vertical median MC axis are small companies, while those to the right are big. Similarly, those above the horizontal 70/BE axes had value stocks and those below 30/BE, growth stock—firms with neutral stocks lie between the two axes.

Equation 14 calculates the size effect as small minus big (SMB):

$$SMB = \frac{1}{3}(SV + SN + BS) - \frac{1}{3}(BV + BN + BG) \tag{14}$$

Equation 15 calculates the value effect as high minus low (HML):

$$HML = \frac{1}{2}(SV + BV) - \frac{1}{2}(SG + BG) \quad (15)$$

To estimate all the hypothesis testing models in the current study, after performing the unit root test, DOLS regression with Newey–West estimation was applied: DOLS tackles simultaneity problems, while Newey–West corrects for autocorrelation and heteroskedasticity. This technique is used, in the main, when some variables are integrated at the order of 1 and others at first difference. In addition, the model was augmented with leads and lags to ensure the findings from this study were applicable at other periods.

4.16. Data and Data Sources

This study employed daily data frequencies from January 1, 2005 to December 31, 2015, which produced 2671 observations. To avoid data-snooping bias, both listed and de-listed firms within the study period were selected: 13 in the financial sector (10 banks and 3 insurance companies) and 11 in the manufacturing sector. The data was extracted from two sources: market data from the GSE and BoG; book value data from the audited financial statements of individually listed firms. Subsequently, the dependent variable, represented by the returns on the portfolio, was constructed mainly from market data, supplemented with accounting data. Similarly, the independent variables, represented by size and value of the firms, were constructed from both market and accounting data. However, the calendar effect variables were based purely on market data.

5. RESULTS AND DISCUSSION

This section presents the data analysis of the listed financial institutions and manufacturing companies from Fama and French's three-factor model.

Table-1. Descriptive statistics for the Fama–French three-factor model.

| Variables | RM–RF | Financial sector | | | Manufacturing sector | | |
|-----------|-----------|------------------|----------|-----------|----------------------|------------|----------|
| | | RPF–RF | LSMB | HML | RPM–RF | LSMB | HML |
| Mean | -0.1758 | -0.1751 | -7.6298 | 0.7400 | -0.1741 | -3.3994 | 26.0767 |
| SD | 0.0668 | 0.0716 | 7.6117 | 0.9183 | 0.1087 | 3.5177 | 34.2992 |
| Skewness | -0.7106 | 3.8714 | -0.7379 | 2.0017 | 27.1689 | -3.2257 | 0.6622 |
| Kurtosis | 9.3191 | 88.3057 | 1.6043 | 8.0637 | 1134.7500 | 11.5985 | 1.6390 |
| JB | 4668.8280 | 816548 | 459.2143 | 4637.2040 | 143080 | 12860.3000 | 401.3806 |
| Obs | 2671 | 2671 | 2671 | 2671 | 2671 | 2671 | 2671 |

Note: SD: standard deviation; JB: Jarque–Bera Test; Obs: observations; RM: total market portfolio return; RF: risk-free rate of return; RP: market risk factor, F = financial, M = manufacturing; SMB (small minus big): size risk factor, L = factor loading; HML (high minus low): book-to-market risk factor

Table 1 shows negative average returns for the market and size risk premiums and financial and manufacturing portfolio returns variables, but positive for value risk premium.

Table-2. Descriptive statistics for dummy variables.

| Dummy variable | Frequency | Percentage |
|----------------|-----------|------------|
| Monday | 523 | 19.5880 |
| Tuesday | 528 | 19.7752 |
| Wednesday | 558 | 20.8988 |
| Thursday | 531 | 19.8876 |
| Friday | 530 | 19.8502 |
| January | 222 | 8.3115 |
| TOM | 521 | 19.5058 |

For the dummy variables, Table 2 shows 523 (19.6%) out of a total of 2,670 observations occurred on Mondays. 222 (8.3% in January, and 521 (19.5%) at the TOM.

5.1. Unit Root Analysis

The augmented Dickey–Fuller (ADF) test was conducted to investigate the stationarity of the variables, as non-stationarity can lead to spurious results.

Table-3. ADF unit root test.

| Variables | ADF level | ADF 1 st diff | Order |
|-----------|------------------|--------------------------|-------|
| RPF–RF | -1.6648 (0.4491) | -23.4933 (0.0000) | I (1) |
| RPM–RF | -4.5184 (0.0002) | | I (0) |
| RM–RF | -1.2477 (0.6557) | -24.2792 (0.0000) | I (1) |
| HML (F) | -3.3028 (0.0149) | | I (0) |
| LSMB (F) | -3.5133 (0.0077) | | I (0) |
| HML (M) | -1.8303 (0.3660) | -60.8873 (0.0000) | I (1) |
| LSMB (M) | -3.5890 (0.0061) | | I (0) |

As can be seen from Table 3, while some variables become stationary at level, others do so at first difference; thus, OLS regression cannot estimate the models in this study. Instead, DOLS regression, which can estimate variables at both level and first difference, was employed.

5.2. Day-of-the-Week Effect and Stock Returns on the Ghana Stock Exchange

Table 4 reports the results for the day-of-the-week effect.

Table-4. Estimation of the day-of-the-week effect.

| Variables | Financial sector | Manufacturing sector |
|-------------------------|---------------------|----------------------|
| RM–RF | 0.9972*** (73.3235) | 0.9478*** (25.9671) |
| LSMB | -0.0006 (-0.8571) | -0.0006 (-1.0000) |
| HML | 0.0018 (1.5000) | -0.0007 (-1.1667) |
| MON | -0.0527* (-1.8821) | -0.1430 (-1.2160) |
| TUE | -0.0564** (-2.1692) | -0.0402 (-1.2884) |
| WED | 0.0240 (1.4286) | 0.2023 (-1.0406) |
| THUR | 0.0121 (0.6368) | -0.0794 (-1.2786) |
| Constant | 0.0127 (1.0948) | 0.0861 (1.1495) |
| R ² | 0.8849 | 0.3595 |
| Adjusted R ² | 0.8817 | 0.3422 |
| Durbin–Watson | 2.0038 | 1.9972 |

Note: ***, $p < 1\%$ significance; **, $p < 5\%$; *, $p < 10\%$.

The coefficients and p-values for the market risk premium in both the financial and manufacturing sectors supported the asset pricing theory, such as the CAPM: the coefficients being significant at the 1% level. This means that the market risk premium undermines efficiency in the market. However, in contrast to Fama and French (1993) the coefficients for size and value risk premiums in respect of the day-of-the-week effect in both sectors were insignificant. As such, when stocks on the GSE can be classified into high- and low-value growth stocks, investors cannot outperform, and therefore cause inefficiency in the market.

Coefficients for the main variables (i.e., days of the week) are also shown in Table 4, and with none being significant at 10%, reveal no effect in the manufacturing sector on the GSE. However, in the financial sector, negative returns were generated on Mondays and Tuesdays, according to the negative coefficients, which are significant at 10% for Mondays and 5% for Tuesdays. It can thus be concluded that day-of-the-week effects on these two days create inefficiency in the GSE for the financial sector—this is considered a market anomaly.

The findings for the manufacturing sector in the current study are inconsistent with those of Georgantopoulos, Kenourgios, and Tsamis (2011) and Islam and Sultana (2015), but consistent with that of Bundoo (2011). Bundoo (2011) also found that when using Fama and French's three-factor model, the day-of-the-week effect largely

disappeared. Moreover, evidence for the day-of-the-week effect in the financial sector was only found for two days in this study.

The negative returns generated on Mondays and Tuesdays are partially consistent with the findings of Gharaibeh and Al Azmi (2015), which revealed that the first and last trading days of the week (i.e., Monday and Friday) generated positive returns with negative returns on the second day (i.e., Tuesday). In addition, with regard to GSE, the findings from this study are partially consistent those of Alagidede and Panagiotidis (2009), which likewise discovered that positive returns were generated on Fridays, although the effect was insignificant, and negative on Mondays and Tuesdays, the lowest on the former, as well as on Wednesdays and Thursdays. However, Mensah et al. (2016) reported no evidence of a day-of-the-week effect on the GSE.

The significant negative returns on Mondays and Tuesdays in the current study can be explained by the information processing hypothesis: weekends allow investors to collate relevant information and reflect on their investment decisions (Abraham & Ikenberry, 1994; cited in Ndungu, 2014). Therefore, earlier negative returns could lead investors to sell rather than buy stocks, meaning supply would exceed demand and result in low, or negative, returns on Mondays and Tuesdays.

Furthermore, the short sale hypothesis can explain negative returns on Mondays: investors close their positions on Fridays and do not actively trade before the weekend, waiting until the following Monday to re-establish their positions (Mensah et al., 2016). Such short-selling results in stock prices rising on Fridays and falling on Mondays.

5.3. January Effect and Stock Returns on the Ghana Stock Exchange

Table-5. Estimation of the January effect.

| Variables | Financial sector | Manufacturing sector |
|-------------------------|---------------------|----------------------|
| RM-RF | 1.0002*** (67.1275) | 0.9528*** (28.6988) |
| LSMB | -0.0004 (-0.5000) | -0.0005 (-0.4167) |
| HML | 0.0013 (1.1818) | -0.0006 (-1.2000) |
| January | 0.0050* (1.9231) | 0.0003 (0.0968) |
| Constant | -0.0007 (0.2500) | -0.0052*** (-2.1667) |
| R ² | 0.8834 | 0.3252 |
| Adjusted R ² | 0.8819 | 0.3149 |
| Durbin-Watson | 1.9853 | 1.9986 |

Note: ***, $p < 1\%$; *, $p < 10\%$.

As can be seen in Table 5, only the market risk premium could explain the variation in the portfolio returns of listed manufacturing companies on the GSE. Compared with the financial sector, which showed both January and market risk premium effects, this sector exhibited relative efficiency in the market. However, neither sector showed significant effects of size (SMB) or value (HML) risk premiums, in contrast to the findings of Bundoo (2011) and Chou, Das, and Rao (2011). Although the market (RM-RF), size, and value risk premiums were only used as control variables in the current study, the results do contribute to the theoretical literature. The significant effect of the market risk premium on the market corresponds to the CAPM, in which the market risk premium is assumed to be a key determinant of the expected market return. It is thus implied that investors' stock returns from financial institutions and manufacturing companies on the GSE is affected by the systematic risk assumed in the CAPM.

Similarly, the results of the size and value risk premiums are compatible with the CAPM, but not Fama and French's three-factor model (1993), which was developed to compensate for the shortfall in the CAPM. Fama and French (1992) introduced the two additional risk factors (i.e., size and value) believed to be important determinants of market returns as common to all stocks. In this study, however, the investigation into the January effect in the financial and manufacturing sectors found no evidence for the applicability of the three-factor model.

The coefficient reported in Table 5 for the January effect identifies it as another market anomaly. Both sectors show positive returns, but only significant in the financial sector ($p = 0.0050$), suggesting that returns on investments in financial institutions on the GSE would be high in January. Thus, this study rejects the null hypothesis, that January exerts no significant effect on stock returns, for financial institutions, though not manufacturing companies.

As investors on the GSE could not earn significantly higher returns than average from manufacturing companies in January, then it cannot be considered a market anomaly and the market can be considered seasonally efficient. Obviously, the opposite is true for the financial sector.

These findings corroborate not only Sarpong's (2015) findings of a significant positive effect in January on the GSE but also Wachira's (2013), which revealed a significant January effect on the Nigerian Stock Exchange. In addition, Chou et al. (2011) posited that and the effects of size and value risk premiums are related to the January effect it was demonstrated that large capital stocks carried a significant value risk premium in January, while a higher such risk occurred in other months for small capital stocks. Consequently, results are likely to reflect varying effects if portfolios are sorted according to size and value.

Earlier empirical studies also produced results consistent with the manufacturing sector experiencing no January effect: although Depenchuk, Compton, and Kunkel's (2010) study in the Ukraine showed that the evidence for the manufacturing sector was likewise not significant; however, they found no January effect in the financial sector either. Similarly, John (2012) found no evidence of the January effect, concluding that no statistically significant relationship with stock returns existed.

It can thus be inferred that the significant January effect in the financial sector is part of the overall calendar effects on the stock market creates seasonal inefficiency in the market. This can be, and frequently is, explained by the tax-loss selling hypothesis, according to which investors gain by selling their stocks that have declined in price at the end of the year to offset the loss against their tax liabilities (Poterba & Weisbemer, 2001; cited in Sarpong, 2015). As Ghanaian tax laws allow losses to be carried over, stock returns would be positive without incurring further tax liabilities.

The variation of the January effect in the financial and manufacturing sectors on the GSE, though, could be because investors do not always act rationally, as assumed by economic theories. Prospect Theory posits that decision-making is based on the level of certainty that the individual will gain or lose as a result; thus, investors would prefer to a smaller but guaranteed return than a higher return that carries the risk of high losses. Consequently, investors tend toward stocks of firms for which substantial data is available to assess the risk–return nexus, but this might not be available in January for all stocks in Ghana and affect the expectation from and performance of some stocks.

5.4. Turn-of-the-Month Effect and Stock Returns on the Ghana Stock Exchange

Table-6. Estimation of the turn-of-the-month effect.

| Variables | Financial sector | Manufacturing sector |
|-------------------------|---------------------|----------------------|
| RM–RF | 1.0042*** (74.3852) | 0.9520*** (27.3563) |
| LSMB | -0.0003 (-0.4286) | -0.0010* (-1.6667) |
| HML | 0.0015 (1.2500) | -0.0006 (-1.2000) |
| TOM | 0.0025 (1.0417) | -0.0210 (-0.9292) |
| Constant | -0.0001 (-0.0455) | -0.0015 (-0.9375) |
| R ² | 0.8817 | 0.3259 |
| Adjusted R ² | 0.8795 | 0.3135 |
| Durbin–Watson | 1.9981 | 2.0006 |

Note: ***, $p < 1\%$; *, $p < 10\%$.

Table 6 shows that the market risk premium plays a significant role in the turn-of-the-month effect in both the financial and manufacturing sectors. The coefficients of 1.004 ($p = 0.0000$) and 0.9520 ($p = 0.0000$) for the financial and manufacturing sectors, respectively suggest that the market risk premium can explain some of the variations in returns from the financial institutions and manufacturing companies.

In the financial sector, the coefficients of the other variables in Table 6 imply that no significant TOM effect exists, and cannot therefore be considered a primary market anomaly for or calendar effect on financial institutions listed on the GSE. In addition, these findings that CAPM but not Fama and French's three-factor model applies for TOM in the financial sector.

In contrast, a negative size risk premium effect (-0.001), significant at 10% ($p = 0.0808$) on the manufacturing sector can be seen in Table 6; though there is still no evidence of a TOM effect. Conversely, large manufacturing companies will thus generate low returns, and smaller companies high returns, for investors.

These results revealed insignificant positive and negative TOM effects on stock returns in the financial and manufacturing sectors, respectively. As such, the findings failed to reject the null hypothesis that the TOM effect exerted no significant effect on stock returns from financial institutions and manufacturing companies listed on the GSE.

The final conclusion is that no TOM effect exists on the GSE: the daily average stock returns on the last trading day of the month and first three of the next do not significantly differ from other trading days in the month for the financial and manufacturing sectors. These findings are partially inconsistent with those of Booth, Kallunki and Martikainen (2001, cited in Tempel, 2009), who also found a positive coefficient for the TOM effect, and Booth, Aivazian, Demirguc-Kunt, and Maksimovic (2001), who found a significant relationship between the TOM effect and stock returns. The current study also contradicts those into the TOM effect by Liu (2013) on the US equity market, Kayacetin and Lekpek (2016) on the Turkish stock market, Mulumbi (2010) on the NSE, and Kumar (2015) on the Indian currency market.

Another explanation for the findings of the current study is offered by the Ogden's liquidity hypothesis, which states that investments are governed by the standard payments calendar. As salaries, interest, and dividends are often paid at the end or start of the month, the increased liquidity of current and prospective investors enhances their purchasing power, upsetting the equilibrium of demand and supply through the increased demand for investments (Burnett, 2017; Tempel, 2009). On the other hand, rational investors who are aware of the rise in stock prices during the last trading day of the month trading and first three of the next may wait to buy stocks at a good price; hence, stock returns could be lower than average, albeit not significantly. However, even those who are not acquainted with this knowledge may not stimulate the volume of trading required to generate significant positive returns, as this study revealed in the financial sector.

Table-7. ARCH model results.

| Series | ARCH (RESID ²) | F-statistic | R ² | P value |
|---------|----------------------------|-------------|----------------|---------|
| DOW (F) | -0.00059 | 0.00096 | 0.000960 | 0.9753 |
| DOW (M) | -0.00039 | 0.00046 | 0.000460 | 0.9839 |
| JE (F) | -0.00061 | 0.00099 | 0.000998 | 0.9748 |
| JE (M) | -0.00038 | 0.00039 | 0.000394 | 0.9842 |
| TOM (F) | -0.00058 | 0.00092 | 0.000928 | 0.9757 |
| TOM (M) | -0.00038 | 0.00039 | 0.000392 | 0.9842 |

Note: DOW: day-of-the-week effect; JE: January Effect.

Stock returns are usually associated with high time-varying volatility, defeating the notion of constant variance. It is thus vital to test for the existence of a time-varying effect (i.e., ARCH Effect), but linear models rarely explain stock market volatility. GARCH models are suitable for estimating time series, though, if the test results indicate heteroskedasticity, but not if the ARCH effect is absent. From Table 7 shows that there was no evidence of conditional heteroskedasticity in the OLS residuals for the three effects studied: none of the p-values are significant

and all the R^2 values are low. Consequently, stock returns from neither the manufacturing or financial sectors exhibit a time-varying effect.

6. CONCLUSION AND RECOMMENDATION

This study investigated the existence of a day-of-the-week, January effect, and TOM effect on the GSE, focusing on the manufacturing and financial sectors. Adopting Fama and French's (1993) three-factor model and analyzing the data through DOLS regression, the results showed evidence of a day-of-the-week effect (negative returns on Mondays and Tuesdays) and January effect in the financial sector only.

Based on the findings of the current study, investors should be advised to time their investments with those periods observed to generate significant returns and formulate investment strategies that will profit from the market anomalies, which undermine the EMH and cast doubt on its authenticity. However, caution should be exercised, as transaction and information costs may prevent investors receiving excess returns, although a simple buy-and-hold strategy and diversified portfolio may be beneficial.

Furthermore, portfolio managers must decide the level of risk to accept in terms of the market, size of firm, and book-to-market ratio, identifying the different sources of risk to each individual firm's stocks. This enables arbitrage opportunities to be maximized at a lower cost: financial stocks can be purchased at a lower price on Mondays and Tuesdays and sold for higher returns in January; purchasing financial shares in January is discouraged.

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