International Review of Business Research Papers
Vol. 12. No. 1. March 2016 Issue. Pp. 171 – 192

Testing Weak Form Efficiency: An International Market Perspective

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The efficient market hypothesis has been given lots of importance in the financial literature. Eventually, the importance of the efficiency of a market is that prices will fully reflect all available information. This study focuses on the weak-form market efficiency testing for three particular stocks (Bel-Fuse-Inc., Berkshire-Hills Bancorp, Inc.-and Beasley Broadcast-Group,-Inc.) and two decile indices (NYSE/AMEX/NASDAQ index capitalization based-Decile-1-and-10). With the aid of autocorrelation testing, variance ratio tests and calendar effects testing, done under the OLS regression as well as the GARCH family models, two indices, DEC1 and DEC10, and three individual stocks, BBGI, BELFA and BHLB, were tested. Validated under both a daily perspective as well as on a monthly one, the returns of BBGI and DEC10 have consistently proven to follow a random walk while DEC1 and BHLB have shown the contrary. They showcased a day-of-the-week effect as well as a month-of-the-year effect. BELFA provided evidences that it does not follow a random walk when tested using daily data but these effects vanished

JEL Codes: C1, G14

1. Introduction

The efficient market hypothesis (EMH) has been considered as very important in the financial literature. Fama (1970) was the first scholar who defined three types of efficient markets among which is the weak-form market efficiency whereby the information subset of interest is past price histories.

The Efficient Market Hypothesis (EMH) is a crucial area of study as the hypothesis that the securities markets are efficient represents the foundation for most research that is made in financial economics. Given its significant implications in the functioning of the financial markets, it shows to be one of the well-researched areas and gives rise to an interesting debate among financial researchers. The efficient-market hypothesis was initially developed by Professor Eugene Fama in the early 1960s, where the efficient market was defined as one where prices fully reflect available information, and suggested three models for testing market efficiency: the Fair Game model, the Random Walk model and the Martingale model Shaker (2013). Later, in 1970, Fama published a re-examination of both the theory and the evidence for the hypothesis. The paper extended and developed the theory, included the definitions for three forms of financial market efficiency: weak, semi-strong and strong.

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There are several studies which have focused on the weak-form as if the evidence is not successful in supporting the weak-form of market efficiency, then it is not essential to examine the EMH at the severer levels of semi-strong and strong form. The weak form EMH assumes that the current market prices will combine all security market information including historical sequence of prices, rates of return, trading volume data & other market generated information (Cuthbertson 2002). It is the last form of efficiency that defines a market as being efficient if current prices fully reflect all information contained in the historical asset prices and a trading rule based on the past prices cannot be developed to identify mispriced assets. This study will focus on the weak-form market efficiency testing for three particular stocks (Bel-Fuse-Inc., Berkshire-Hills Bancorp, Inc.-and Beasley Broadcast-Group,-Inc.) and two decile indices (NYSE/AMEX/NASDAQ index capitalization based-Decile-1-and-10).

This paper is organized as follows. Section 2 presents the literature review followed by section 3 which introduces the methodology used. Then Section 4 discusses the empirical findings. Afterwards, section 5 concludes on the research work.

2. Literature Review

The EMH tries to explain why stock market prices appear to follow a *random walk.* According to Fama (1970) an efficient market is a market in which prices reflect all available information. The intrinsic value of a share is measured by the future discounted value of cash flows that will accrue to the investors. Share prices must reflect all available information if the stock market is efficient. This is necessary for the evaluation of a company's future performance therefore the market price of share must be equal to its intrinsic value. Any new information which might change the future profitability of the company must be immediately reflected in the share price. Else, if there is any delay in the diffusion of information to price this would result in irrationality, as some of this available information could be exploited to forecast future profitability. Thus, in an efficient market, price changes must be a response only to new information. Share prices must fluctuate unpredictably since information arrives randomly. The Random Walk model can be stated in the following equation:

$$P_{t+1} = P_t + \varepsilon_{t+1}$$

Where

P_{t+1}: price of share at time t+1;
P_t : price of share at time t;
ε_{t+1}: random error with zero mean and finite variance.

The above equation indicates that the price of a share at time t+1 is equal to the price of a share at time t plus given value that depends on the new information (unpredictable) arriving between time t and t+1. In other word, the change of price, $\varepsilon_{t+1} = P_{t+1} - P_t$, is independent of past price changes.

Fama (1970) argued that the random walk model is an extension of the expected return or fair game model. Specifically, the fair game model just indicates that the conditions of market equilibrium can be stated in terms of expected returns while the random walk model gives the details of the stochastic process generating returns. Therefore, he concluded that empirical tests of the random walk model are more powerful in support of the EMH than tests of the fair game model.

2.1 Empirical Review

A study was conducted by Kenourgios and Samitas (2008) on the Athens Stock Exchange (ASE) General Index. Daily stock returns over a period of ten years were used. The sample was divided into two subperiods: 1995-2000 and 2001-2004. In the first sub periods three major indices was also considered namely banking, insurance and miscellaneous while for the second period FTSE-20 and FTSE-40 was examined. The authors tested for possible existence of day of the week using the GARCH (1,1) and Modified-GARCH (1,1) model.

The findings indicated the presence of such anomaly over the period 1995-2000. However, due to the Greek entry to the Euro-Zone and the market has developed into an upgraded one; this stock market anomaly seemed to lose its strength over the period 1995-2000 in the ASE.

In a study undertaken by Giovanis (2009), he analysed the month of the year and January effect from fifty-five stock market indices located into fifty-one countries. The symmetric GARCH as well as the asymmetric GARCH models were estimated. In order to estimate regression the GARCH models were applied.

The first model is the simple symmetric GARCH (1,1) recommended by Bollerslev (1986) and is as follows

$$\varepsilon_t \sim (0, \sigma_t^2)$$

Where ε_t is the disturbance term of the mean equation and

$$\sigma_t^2 = \omega + a_0 u_{t-1}^2 + a_1 \sigma_{t-1}^2$$

The standard GARCH model is symmetric in its response to past innovations. Good news and bad news may have different effects on the volatility thus two alternative GARCH models were estimated in order to capture the asymmetric nature of volatility responses.

The asymmetric EGARCH and GJR models were the other two GARCH models considered Nelson (1991) proposed the EGARCH (1,1) model and was defined as:

$$\varepsilon_t \sim (0, \sigma_t^2)$$

$$\log(\sigma_t^2) = \omega + \log a_0 (\sigma_{t-1}^2) + a_1 \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \gamma \frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}$$

where ε_t is the disturbance term of the mean equation. It is expected $\gamma < 0$, "good news" generate less volatility than "bad news", where γ reflects the leverage effect.

The second asymmetric GARCH model estimated was the GJR-GARCH (1,1). This was proposed by Glosten et al. (1993)

$$\sigma_t^2 = \omega + a_0 u_{t-1}^2 + a_1 \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$$

I_{t-1} is a dummy variable, where $I_{t-1} = 1$ if $u_{t-1}^2 < 0$ and $I_{t-1} = 0$ otherwise. Also for a leverage effect is expected that $\gamma > 0$, so that the "bad news" have larger impacts, and is required that $\propto_1 + \gamma \geq 0$ and $\propto_1 \geq 0$ for non-negativity condition.

Empirical findings suggested evidence of December effect on twenty stock markets, February effect is found in nine stock markets, January effect in seven stock markets while an April six stock markets. This suggested that the returns on those specific months are higher than the remaining months.

3. Data and Methodology

3.1 Data Description

The data used in this study consist of daily and monthly returns of the three stocks and two decile indices described in Figure 1. All price data are obtained over the period from January 2008 to December 2011 from the-Centre-for-Research-in-Securities-Prices-database-(CRSP), therefore 1044 observations of daily returns and 48 observations of monthly returns. Then, a natural-logarithmic transformation is performed on the primary data to obtain logarithmic returns which is used for the whole study.

3.2 Methodology

A set of complementary tests are used to detect the random walk in the observed series of the stocks and indices.

Tests for Weak Form Efficiency

The primary approach is a set of tests for weak-form efficiency. Firstly, the autocorrelation test was undertaken to measure the relationship between the stock return at current period and its value in the previous period aiming to determine whether the serial correlation coefficients are significantly different from zero. Statistically, the hypothesis of weak-form efficiency should be rejected if stock returns are serially correlated. To test the joint hypothesis that all autocorrelations are simultaneously equal to zero, the Ljung–Box statistic is used.

Secondly, to test whether the data shows any seasonal effects over days of the week, the following regression has been run:

$$r_t = \gamma_{Mon} D1_t + \gamma_{Tues} D2_t + \gamma_{Wed} D3_t + \gamma_{Thu} D4_t + \gamma_{Fri} D5_t + \varepsilon_t \quad (1)$$

where

$D1_t = 1$ if it is a Monday return or otherwise zero

Likewise, to test for any seasonal effects over months of the year, the following regression has been run:

$$r_t = \gamma_{Jan} D1_t + \gamma_{Feb} D2_t + \ldots + \gamma_{Nov} D11_t + \gamma_{Dec} D12_t + \varepsilon_t \quad (2)$$

where
$D1_t$ = 1 if it is a January return or otherwise zero

Furthermore, another regression which incorporates a crisis dummy has also been run for both calendar effects as follows:

$$r_t = \gamma_{Mon} D1_t + \gamma_{Tues} D2_t + \gamma_{Wed} D3_t + \gamma_{Thu} D4_t + \gamma_{Fri} D5_t + \gamma_{Crisis} D6_t + \varepsilon_t \quad (3)$$
$$r_t = \gamma_{Jan} D1_t + \gamma_{Feb} D2_t + \ldots + \gamma_{Nov} D11_t + \gamma_{Dec} D12_t + \gamma_{Dec} D13_t + \varepsilon_t \quad (4)$$

To protect against the dummy variable trap, the above regressions exclude intercept terms.

Finally, the variance ratio test, proposed by Lo and MacKinlay (1988) will be employed. It is based on the assumption that the variance of increments in the random walk series is linear in the sample interval. Specifically, if a series follows a random walk process, the variance of its q-differences would be q times the variance of its first differences.

3.3 Volatility Modelling

The second approach is an estimation of GARCH models. Hence, the changing variance is included into estimation. A modified GARCH (1,1) specification with added dummy variables for each day-of-the-week and month-of-the-year in the conditional variance equation is used to include the calendar effects for both the return and volatility equations. Also, to prevent the problem of collinearity in the regression model, only 4 out of 5 days in the week are included in the conditional variance equation as follows:

$$r_t = \gamma_{Mon} D1_t + \gamma_{Tues} D2_t + \gamma_{Wed} D3_t + \gamma_{Thu} D4_t + \gamma_{Fri} D5_t + \varepsilon_t \quad (5)$$
$$\sigma_t^2 = \alpha_0 + \gamma_{Tues} D2_t + \gamma_{Wed} D3_t + \gamma_{Thu} D4_t + \gamma_{Fri} D5_t + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} + \sum_{j=1}^{p} \alpha_j \varepsilon^2_{t-j} \quad (6)$$

The same technique was applied for the month-of-the-year effect as follows:

$$r_t = \gamma_{Jan} D1_t + \gamma_{Feb} D2_t + \ldots + \gamma_{Nov} D11_t + \gamma_{Dec} D12_t + \varepsilon_t \quad (7)$$
$$\sigma_t^2 = \alpha_0 + \gamma_{Feb} D2_t + \gamma_{Mar} D3_t + \ldots + \gamma_{Nov} D11_t + \gamma_{Dec} D12_t + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} + \sum_{j=1}^{p} \alpha_j \varepsilon^2_{t-j} \quad (8)$$

Similarly, a financial crisis dummy has been included in both equations and run at the same time as follows:

$$r_t = \gamma_{Mon} D1_t + \gamma_{Tues} D2_t + \gamma_{Wed} D3_t + \gamma_{Thu} D4_t + \gamma_{Fri} D5_t + \gamma_{Crisis} D6_t + \varepsilon_t \quad (9)$$
$$\sigma_t^2 = \alpha + \gamma_{Tues} D2_t + \gamma_{Wed} D3_t + \gamma_{Thu} D4_t + \gamma_{Fri} D5_t + \gamma_{Crisis} D6_t + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} + \sum_{j=1}^{p} \alpha_j \varepsilon^2_{t-j} \quad 10)$$

$$r_t = \gamma_{Jan} D1_t + \gamma_{Feb} D2_t + \ldots + \gamma_{Nov} D11_t + \gamma_{Dec} D12_t + \gamma_{Crisis} D13_t + \varepsilon_t \quad (11)$$
$$\sigma_t^2 = \alpha_0 + \gamma_{Feb} D2_t + \gamma_{Mar} D3_t + \ldots + \gamma_{Nov} D11_t + \gamma_{Dec} D12_t + \gamma_{Crisis} D13_t + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} + \sum_{j=1}^{p} \alpha_j \varepsilon^2_{t-j} \quad (12)$$

Remarkably it has been observed that negative returns are followed by higher volatility than positive returns thus tending to be asymmetrical in nature. To account for this behaviour, the EGARCH (Nelson, 1991) models are also estimated as follows:

$$\log \sigma_t^2 = \alpha_0 + \sum_{j=1}^{p} \alpha_j \frac{|\varepsilon_{t-j}|}{|\sigma_{t-j}|} + \gamma \frac{\varepsilon_{t-j}}{\sigma_{t-j}} + \sum_{j=1}^{p} \beta_j \log\sigma_{t-j}^2 + \gamma_{Tues} D2_t + \gamma_{Wed} D3_t + \gamma_{Thu} D4_t + \gamma_{Fri} D5_t \quad (13)$$

The Threshold GARCH (TGARCH) model by Zakoian (1993) also models asymmetry in the ARCH process and the specification is one on conditional standard deviation instead of conditional variance. A regression was run as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k} + \gamma_{Tues} D2_t + \gamma_{Wed} D3_t + \gamma_{Thu} D4_t + \gamma_{Fri} D5_t \quad (14)$$

4. Empirical Findings

4.1 Tests for Weak Form Efficiency

4.1.1 Autocorrelation Tests

To test the weak-form of EMH, first the autocorrelation tests with 8 and 6 lags are performed for daily and monthly returns of the constituents.

4.1.1.2 Results for Daily Log Returns

From Table I, Panel A, it is found that the null hypothesis of random walk is rejected for all studied series using daily returns. Specifically, for DEC1, it is evident that autocorrelation coefficients are significant with a positive sign up to the 4th lag. Remarkably, the positive sign of the autocorrelation coefficients indicates that consecutive daily returns tend to have the same sign, so that a positive (negative) return in the current day tends to be followed by an increase (decrease) of return in the next several days. Particularly, the results of the Ljung-Box reveal that the autocorrelation coefficients of all 8 lags are jointly significant at 1% and 5% level. For the individual stocks and DEC10, it is observed that serial correlation coefficients are significant at 1st, 5th and 7th lag for BBGI, at 1st and 5th lag for BHLB and at 1st lag for BELFA and DEC10. Notably, the results of Q-test fail to support the joint null hypothesis that all autocorrelation coefficients of 8 lags are equal to zero for the three stocks and DEC10 at 5% level.

4.1.1.3 Results for Monthly Log Returns

Unlike the results for the daily returns, it is found that autocorrelation coefficients of the monthly returns for DEC1 are significant with a positive sign only at the 1st lag. However, based on the Q-statistics, the null hypothesis of no autocorrelation on the DEC1 returns for all the 6 lags is strongly rejected at the 1% level concluding that DEC1 still seems to be affected by past return information to some extent. Furthermore, results of the autocorrelation tests on monthly returns for BHLB show significant autocorrelation coefficient at the 1st lag similar to its daily log returns and hence does not contribute towards weak-form efficiency. On the contrary, the autocorrelation coefficients of the monthly log returns for BBGI and BELFA are insignificant, unlike their daily log returns, and the Q-statistics support the joint null hypothesis that all autocorrelation coefficients from lag 1 to 6 are equal to zero. Therefore, here it can be concluded that BBGI and BELFA are both weak-form efficient. Notably, for DEC10, there is significant autocorrelation at lag 6 while the result of the Ljung-Box is significant at lag 4 and 6. Nevertheless, this result does not bring any economic significance.

4.1.1.4 Results for Squared Log Returns

From the empirical results for the squared returns of daily and monthly log returns, the random walk hypothesis is strongly rejected for both indices and all stocks for the daily frequencies. Additionally, the joint hypothesis that all autocorrelation coefficients are simultaneously equal to zero is significant for all 8 lags. This demonstrates non-stationarity in the data and as squared returns is a proxy for variance, heteroskedasticity may be present.

However, the rejection of the null hypothesis is less pronounced for the monthly frequencies as BHLB and DEC10 exhibit no serial autocorrelation. As far as DEC1 and BELFA are concerned, there is autocorrelation at the 1st lag only, unlike their daily frequencies, while the Q-tests reject the null up to lag 6, similar to their daily frequencies. In such a context, this behaviour can be related to the fact that the returns are relatively white noise. This holds true for BBGI as well since there is serial autocorrelation at lag 3 while its Q-statistics is insignificant at all a lag.

The overall autocorrelation tests have proved that DEC10 and BHLB may follow a random walk while DEC1 may be weak-form inefficient with possible presence of heteroskedasticity both at the daily and monthly level. However, BELFA and BBGI have shown that they can be slightly weak-form efficient by looking at their monthly returns.

4.2 Day of the Week Effect

From the regression results testing for the presence of day-of-the-week effect, none of the coefficients are significant at the 5% level. Economically, this means that no day-of-the-week effect is observed for the stocks and the indices. On the other hand, when a dummy in included for the crisis, the results change considerably and is better explained, proven by the increased adjusted R-squared.

The crisis variable is noted to be significant for the indices and for BHLB. This sounds reasonable as the industry of BHLB (which is the banking sector) is bound to be affected by the financial crisis. Remarkably, it explains 10% of the variations in the daily returns of BHLB. After accounting for the volatility caused by the crisis, the Monday coefficient of BHLB is found to be significant, being a negative low coefficient of -0.18%. This result therefore is in line with numerous empirical evidences existing in the literature where Monday returns are usually lower (Cho et al., 2006). This led to the conclusion that BHLB is demonstrating weak-form inefficiency here. Similarly, for BELFA, the variation of its returns is at -0.68% on Mondays. However, its crisis coefficient is insignificant explained by the fact that the electronics industry has not been affected by the crisis.

Moreover, the Friday coefficient of DEC1 has proved to be significant at the 5% level with a positive return of 0.24% in daily frequencies after accounting for the volatility brought by the crisis and as advocated by Lenkkeri et al.(2006), Fridays are known to experience positive returns. Therefore, DEC1 tends to show weak-form inefficiency. Despite, after accounting for the volatility caused by the crisis in the stock market, DEC10 and BBGI are still at the same conclusion that they are weak-form efficient.

4.3 Month of the Year Effect

From further analysis, it is evident that no month-of-the-year effect exists for the constituents, except for BHLB, as no coefficients are significant at the 5% level. BHLB has shown significant coefficients for January and December being at 14.5% and -8.9% respectively. Likewise, the regression was run a second time with the inclusion of a variable for the event of the crisis. BHLB has again reported a significant coefficient for January at 14.9% and the crisis has shown to explain 1.6% variation in its monthly log returns. Likewise, DEC1 has reported a January effect with a positive coefficient of 9.4% and a negative significant coefficient of -0.06% for the crisis variable. Both these stocks are in line with what the literature mentions about the January effect (Wachtel, 1942). However, the January effect is associated with small companies whereas DEC1 includes the highest capitalisation stocks listed on the NYSE. Additionally, a negative coefficient of -5.9% is significant during April and numerous academics blame tax-loss selling as being drivers of an April effect in the stock market (Chen et al., 2006).

Furthermore, the crisis variable has reported to be significant for DEC10 as well, explaining 5.2% variations of its monthly log returns. On the contrary, BELFA, DEC10 and BBGI neither showed any seasonal effects nor seemed to be affected by the crisis and therefore can be concluded being weak-form efficient in such a scenario while BHLB and DEC1 exhibited some month-of-the-year effect.

4.4 Variance Ratio Tests

This study employs variance ratio tests for both null hypotheses, namely the homoscedastic and heteroscedastic increments random walk and calculated for intervals of 2, 4, 8 and 16 observations.

4.4.1 Daily Variance Ratio Tests

Referring to the empirical evidence obtained from the variance ratio tests for daily log prices indicates that the random walk hypothesis-(RW1) under the assumption of homoscedasticity is rejected for all series except at lag 16 for BELFA and DEC10. In the case of BBGI, BHLB and DEC1, for instance, the Z-statistics suggest that the variance ratios are significantly different from one for all intervals at the 5% level. Therefore, the null hypothesis of random walk-(RW1) is strongly rejected for these series. Similarly, the empirical findings reveal that the null hypothesis-(RW1) of random walk for BELFA and DEC10 cannot be accepted for all levels of q at the 5% level of significance.

However, the rejections of the random walk hypothesis-(RW3) under heteroscedasticity assumptions for DEC10 and BBGI changes. Undeniably, $Z^*(q)$ are significant at all lags for

BHLB and DEC1 failing to reject the null of random walk-(RW3). Moreover, the evidence against the null under the assumption of heteroscedasticity in the case of BELFA is weak because only two rejections are reported. On the contrary, BBGI and DEC10 strongly fail to reject the null-(RW3) at 5% level hence proving to follow a random walk under such circumstances.

4.4.2 Monthly Variance Ratio Tests

Results of the variance ratio tests on the monthly log prices confirm again that the null hypothesis of random walk-(RW1) under the assumption of homoscedasticity is rejected for the indices at all cases of q. However, the individual stocks fail to reject the null hypothesis and therefore incline towards the random walk theory. Additionally, the heteroscedasticity variance ratio test provides consistent evidence that the null hypothesis of random walk-(RW3) cannot be accepted for all monthly return series. The indices again reject the random walk hypothesis-(RW3) under all lags while the stocks fail to reject the null concluding that they follow a random walk under monthly prices.

4.5 Volatility Modelling

4.5.1 Diagnosing for ARCH Effects

From the residuals from the OLS regression, used to diagnose ARCH effects for the daily returns, reports significant autocorrelation for-all-the-stocks-and-indices at all lags and the Ljung-Box test proves the same. Conversely, these ARCH effects are reduced when they are modelled under regressions that take into account volatility. This holds true for EGARCH and TGARCH and under the MGARCH model, some autocorrelation remains up to lag 2 for the indices. However, given-this-autocorrelation-is-low, the selection of a GARCH-(1,1) is-quite-satisfactory. Likewise, the LM-ARCH test proves to be significant under the OLS estimation but disappears under the GARCH family for all stocks except DEC10. Additionally, the Jarque-Bera statistics is rejected under all models, concluding that the residuals do not follow normal distribution, but it improves under GARCH models. Therefore, the GARCH family models assess the day-of-the-week effect better than the linear estimation whereby several misspecifications are found.

Furthermore it has been observed that the month-of-the-year models show different results. Under both the squared residuals autocorrelation and the ARCH-LM statistics, the OLS estimation does not bring in any ARCH problems similar to the GARCH models. Importantly, normality of the residuals is respected under all modelling approach.

4.6 Basic GARCH Models

Remarkably, the appropriateness of the GARCH family models is accentuated. From the results of the basic GARCH model, it is clear that the ARCH and GARCH coefficients are highly significant at the 5% level. Importantly, the GARCH coefficients being close to one project the fact that the conditional variance is moving away from its mean and will in turn last for a longer time period. Again, the GARCH model is proven to be effective. Similar conclusion is reached after running a basic EGARCH regression on the daily data. Additionally, the asymmetric coefficient has proven to be significant for BHLB and DEC10 showing leverage effects but these shall be analysed in more detail under other models.

4.6.1 Modified GARCH Model

On a first note, it is vital to understand that when the sum of the significant coefficients on the lagged squared error-(ARCH) and lagged conditional variance-(GARCH) is close to 1, it implies that there is volatility clustering-whereby shocks-will-be persistent (Cont, 2005). This has been observed in all three GARCH models used.

4.6.2 Day of the Week Effect

The results are presented in Table 1 and two regressions were run, one with the crisis variable and one without it. Both indices showed negative significant returns on Mondays, unlike reported under the OLS model, and DEC1 has significant negative return on Tuesday as well with a positive significant return on Friday. Even BHLB has a significant negative return on Monday. Surprisingly, the Monday effect noted for BELFA has disappeared under the volatility model and is showing significant positive return on Friday instead.

Considering the variance equation, the ARCH and GARCH coefficients are significant at 5% level for all constituents proving that the GARCH model is valid. The sum of these two coefficients, being nearly 1, reports the momentum effects that existed during the crisis especially for the indices and BHLB as it in the financial industry. Furthermore, BHLB, BBGI and DEC1 exhibit positive volatility on Monday while negative volatility is observed on Friday for the same stocks. However, the volatility is very small, being close to zero. BELFA and DEC10 exhibited no volatility and the reason for the latter can be explained by the fact that indices are usually well diversified.

Table 1
GARCH Regression Results for Day of the Week Effect

	BBGI		BELFA		BHLB		DEC1		DEC10	
	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*
Mean										
Monday	0.001	-0.005	-0.001	-0.003	0.001	-0.000*	0.000	-0.001*	0.001	-0.002*
Tuesday	-0.002	-0.004	-0.001	-0.003	-0.001	-0.002	-0.000	-0.002*	0.001	-0.001
Wednesday	-0.001	-0.004	-0.001	-0.003	0.000	-0.001	0.001	-0.001	0.001	-0.001
Thursday	-0.009	-0.003	-0.001	-0.003	-0.000	-0.002	0.000	-0.001	0.001	-0.000
Friday	-0.001	-0.004	0.001	0.001*	0.000	-0.001	0.001*	0.001*	-0.000*	-0.001
Crisis		0.005		0.003		0.002		0.002*		0.002*
Variance										
Constant	0.000	0.001*	-0.000	-0.000	0.000	0.000*	0.000*	0.000*	-0.000*	0.000
Tuesday	-0.001	-0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000*	0.000
Wednesday	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000*	-0.000*	-0.000
Thursday	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000*	-0.000
Friday	0.000	0.000	0.000	0.000	0.000	-0.000*	-0.000*	-0.000*	-0.000*	0.000
Crisis		-0.001*		0.000		-0.000*		0.000		-0.000
V_a	0.276*	0.213*	0.127*	0.205*	0.211*	0.149*	0.151*	0.161*	0.184*	0.105*
V_b	0.759*	0.722*	0.864*	0.750*	0.772*	0.834*	0.837*	0.825*	0.689*	0.886*
DOF	*3.104**	*3.241**	*4.233**	*4.195**	*5.765**	*5.991**	*6.386**	*6.276**	*19.997**	*6.939**

4.6.3 Month of the Year Effect

Reported in Table 2, it is clear that BHLB exhibits positive return in January, similar to the OLS results, and likewise DEC1 shows a negative significant return in April. However, some results not shown under the OLS model is that there is significant negative return in June for BBGI and DEC1. This may be due to the disclosure of interim reports around that period of the year causing a June effect. Moreover, no volatility is experienced for any of the stocks or indices as expected for low frequency data.

Table 2
GARCH Regression Results for Month of the Year Effect

	BBGI		BELFA		BHLB		DEC1		DEC10	
	Ƴ	Ƴ*	Ƴ	Ƴ*	Ƴ	Ƴ*	Ƴ	Ƴ*	Ƴ	Ƴ*
Mean										
January	-0.06	0.03	-0.09	-0.07	0.15*	0.15*	0.04	0.09	0.00	0.00
February	-0.04	0.06	-0.04	0.00	-0.04	-0.02	0.01	0.03	0.02	0.01
March	0.05	0.09	-0.02	0.06	0.05	0.06	0.01	0.04	0.02	0.06
April	0.21	0.21	-0.01	0.06	0.02	0.04	-0.03*	-0.05*	0.03	-0.06
May	-0.10	-0.10	-0.06	-0.04	-0.02	-0.04	-0.01	0.02	-0.02	0.02
June	-0.08*	-0.08*	0.01	0.03	-0.03	-0.01	-0.02*	-0.01*	-0.04	-0.03
July	0.09	0.12	0.07	0.12	0.06	0.06	-0.01	0.01	0.02	0.04
August	-0.12	-0.09	-0.01	-0.01	-0.03	-0.04	-0.03	0.01	-0.02	0.01
September	-0.10	-0.10	-0.01	0.04	0.01	0.01	-0.01	-0.01	-0.01	0.01
October	-0.03	-0.01	-0.01	-0.01	-0.03	-0.03	-0.02	-0.03	-0.01	0.01
November	-0.14	-0.02	0.00	-0.01	0.01	0.01	-0.03	-0.04	0.03	0.02
December	0.18	0.16	0.08	0.09	0.10*	0.09	0.04*	0.05*	0.03	0.04
Crisis		-0.12		-0.09		-0.02		-0.07*		-0.05*

Variance

Constant	0.05	0.05	0.02	0.02	0.01	0.01	0.01	0.01	0.03	0.01
February	-0.08	-0.09	0.01	0.01	-0.01	-0.01	-0.01	-0.01	-0.03	-0.01
March	0.05	0.02	-0.03	-0.01	-0.03	-0.00	-.001	-0.00	-0.00	-0.00
April	-0.058	-0.047	-0.020	-0.024	-0.010	-0.01	-0.01	-0.01	-0.00	-0.00
May	-0.04	-0.05	-0.07	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	0.00
June	-0.05	-0.05	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.03	-0.03
July	-0.03	-0.04	0.02	0.01	-0.06	-0.00	-0.00	-0.04	-0.01	-0.00
August	0.01	0.01	-0.03	-0.02	-0.01	-0.01	-0.0	0.00	-0.03	0.00
September	0.01	-0.01	-0.02	-0.02	0.01	0.01	0.04	0.00	0.00	0.00
October	-0.09	-0.08	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.01	0.00
November	0.01	-0.04	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
December	0.05	0.02	-0.02	-0.02	-0.02	0.04	-0.04	-0.05	-0.03	-0.01
Crisis		0.02		0.00		0.00		-0.00		-0.00
Va	0.05	0.09	0.22	0.09	0.08	0.07	0.33	0.21	0.18	0.06
Vb	0.505	0.529	0.449	0.504	0.689	0.62	0.51	0.50	0.56	0.48
DOF	*77.38*	*31.69*	*35.82*	*21.63*	*20.91*	*20.2*	*22.3*	*20.10*	*22.12*	*20.51*
Log Likelihood	*15.54*	*18.33*	*41.81*	*43.03*	*64.19*	*63.7*	*68.2*	*75.69*	*81.71*	*83.21*

4.7 EGARCH and TGARCH Models

While MGARCH is run under symmetric volatility assumption, EGARCH and TGARCH both have asymmetric volatility assumption.

4.7.1 Day of the Week Effect

The results under the EGARCH model exhibited in Table 3 show that the mean equation results are similar to those under the MGARCH model. BHLB, DEC1 and DEC10 still exhibit negative significant returns on Mondays while BELFA has a significant positive return of 0.2% on Friday. Likewise, the variance equation mirrors the results of the MGARCH model but with higher magnitude. BBGI and BHLB report high positive volatility on Monday around 80%. They also report negative volatility on Fridays which is in line with Harvey and Whaley (1992)'s findings that 'many traders close their positions before the weekend and this selling pressure cause the volatility to decline on Fridays while on Mondays traders reopen their positions and this buying pressure cause the volatility to rise'. DEC1 also has the same results for Monday and Friday, however it shows an additional huge negative significance on Wednesday. They attribute this to the fact that traders tend not to take positions in the earlier part of the week and accumulate private information to get a feel for the market, and begin actively take positions in the later part of the week.

As regards the asymmetric terms for BHLB and DEC10, they report significant negative leverage reactions of -8.4% and -15.1% respectively concluding that usually small firms exhibit these leverage effects.

TABLE 3
EGARCH Regression Results for Day of the Week Effect

	BBGI		BELFA		BHLB		DEC1		DEC10	
	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*
Mean										
Monday	0.001	-0.002	-0.001	-0.003	0.001	-0.001*	0.000	-0.001*	0.001	-0.001*
Tuesday	-0.002	-0.003	-0.002	-0.004	-0.001	-0.003	-0.000	-0.002*	0.000	-0.002
Wednesday	-0.001	-0.004	-0.002	-0.004	0.000	-0.003	0.001	-0.000	0.001	-0.002
Thursday	-0.000	-0.003	-0.002	-0.004	0.000	-0.002	0.000	-0.001	0.001	-0.001
Friday	-0.002	-0.004	-0.000	0.002*	0.000	-0.002	0.001*	-0.000	0.000	-0.002
Crisis		0.003		0.003		0.003		-0.002*		-0.003*
Variance										
Constant	0.624*	0.874*	-0.285	-0.287	0.665*	0.822*	-0.117	0.121*	-0.090	-0.098
Tuesday	-0.142	-0.132	0.277	0.302	0.236	0.237	-0.461	-0.481	-0.064	-0.056
Wednesday	-0.003	0.001	0.025	0.021	-0.189	-0.208	-0.558*	-0.552*	-0.249	-0.242
Thursday	-0.090	-0.092	0.155	0.169	0.085	0.095	-0.273	-0.303	-0.031	-0.014
Friday	-0.272	-0.254*	-0.054	-0.045	0.022	-0.002*	-0.778*	-0.779*	-0.404	-0.415
Crisis		-0.114*		-0.008		-0.088*		-0.009		-0.036*
Va(ARCH)	0.492*	0.545*	0.134*	0.128*	0.339*	0.346*	0.302*	0.301*	0.124*	0.119*
Vd(Asymmetric)	-0.010	-0.009	-0.109	-0.108	-0.081*	-0.084*	-0.011	-0.010	-0.144*	-0.151*
Vb(GARCH)	0.920*	0.867*	0.983*	0.983*	0.949*	0.919*	0.968*	0.965*	0.984*	0.980*
DOF	*3.148**	*3.303**	*4.332**	*4.332**	*6.300**	*6.461**	*6.749**	*6.425**	*7.747**	*8.231**
Log Likelihood	*1393.3*	*1397.4*	*2074.9*	*2076.1*	*2399.6*	*2405.2*	*3416.5*	*3424.7*	*3007.0*	*3012.4*

Reported in Table 4, the results under the TGARCH model reflects the same day-of-the-week effects-for BELFA, BHLB and DEC1, but-surprisingly the Monday effect for DEC10 has-now-disappeared. The-results under the variance-equation has shown that-the-volatility noted on Monday and Friday for BBGI has disappear while those for BHLB and DEC1 still exists at the 5% level. Conversely, the significant-variances found under the EGARCH model disappeared for BBGI, BHLB and DEC1. Remarkably, the-leverage effects-under the TGARCH model minimizes for both BHLB and DEC10.

TABLE 4
TGARCH Regression Results for Day of the Week Effect

	BBGI		**BELFA**		**BHLB**		**DEC1**		**DEC10**	
	ϒ	**ϒ***	**ϒ**	**ϒ***	**ϒ**	**ϒ***	**ϒ**	**ϒ***	**ϒ**	**ϒ***
Mean										
Monday	0.001	-0.001	-0.001	-0.002	0.001	-0.001*	0.000	-0.001*	0.001	-0.000
Tuesday	-0.002	-0.004	-0.002	-0.003	-0.001	-0.003	-0.000	-0.002	0.001	-0.001
Wednesday	-0.002	-0.003	-0.002	-0.003	0.000	-0.002	0.001	-0.001	0.001	-0.001
Thursday	-0.002	-0.003	-0.002	-0.003	-0.000	-0.002	0.000	-0.001	0.001	-0.001
Friday	-0.001	-0.003	-0.000	0.001*	0.000	-0.002	0.001	-0.000	0.000	-0.001
Crisis		0.003		0.002		0.002		0.002*		0.002
Variance										
Constant	0.000	0.001	-0.000	-0.000	0.000	0.000	0.000	0.000*	0.000*	-0.000
Tuesday	-0.001	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000*	0.000
Wednesday	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000*	0.000
Thursday	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000*	-0.000
Friday	0.000	0.000	0.000	0.000	0.000	0.000	0.000*	-0.000*	-0.000*	0.000
Crisis		-0.000		0.000				0.000		-0.000
Va(ARCH)	0.287	0.298	0.011	0.015	0.151*	0.153	0.153*	0.160*	0.124*	-0.021
Vd(Asymmetric)	-0.015*	-0.016	0.185	0.192	0.116	-0.045*	-0.004	0.000	-0.144*	-0.100*
Vb(GARCH)	0.757*	0.720	0.900*	0.889*	0.774*	0.745	0.837*	0.825*	0.984*	0.921*
DOF	*3.103**	*3.243**	*4.394**	*4.319**	*5.995**	*6.137**	*6.368**	*6.277**	*19.998*	*8.566**
Log Likelihood	*1389.9*	*1392.2*	*2071.7*	*2073.7*	*2397.2*	*2402.7*	*3414.2*	*3424.1*	*2920.0*	*3008.9*

4.7.2 Month of the Year Effect

Table 5 shows the EGARCH results testing for Month-of-the-Year Effect and similar to the MGARCH results, the same significant months are noted for BBGI, BHLB and DEC1 but overlapping other months as well. BBGI has got negative significant returns not only for May but for June and July also while BHLB has extended to august. BHLB further showed positive significant returns for January, February and December. Moreover, DEC1 reported a positive significant return for December and the negative return in June has been extended to July.

TABLE 5
EGARCH Regression Results for Month of the Year Effect

	BBGI		**BELFA**		**BHLB**		**DEC1**		**DEC10**	
	ϒ	**ϒ***	**ϒ**	**ϒ***	**ϒ**	**ϒ***	**ϒ**	**ϒ***	**ϒ**	**ϒ***
Mean										
January	-0.147*	-0.118	-0.075	-0.114	-0.075	0.128*	0.055*	0.076	-0.038*	0.008
February	-0.038	0.028	-0.012	0.105	-0.012	0.060*	-0.004	0.044	0.014	0.038
March	0.177*	0.180	-0.060*	0.037	0.076*	0.025	-0.033	0.005	0.013	0.053
April	0.123	0.121	0.011	0.102	0.043	0.027	0.013	-0.050*	0.045	0.084
May	-0.062	-0.105*	-0.030	-0.072	-0.016*	0.086	-0.009	0.059	-0.003	0.068
June	-0.139*	-0.166*	0.029*	0.021	-0.030	0.013	-0.011	-0.007*	-0.031	-0.019
July	0.124	-0.138*	0.060	-0.115	0.085*	-0.035*	-0.007	-0.010*	0.033	0.045
August	-0.091	0.009	0.023	0.047	-0.092*	-0.020*	-0.056	0.012	-0.009	0.029
September	-0.012	0.006	-0.020	0.055	0.067*	0.029	-0.001	-0.004	-0.026	-0.036
October	-0.135*	-0.159	-0.023	-0.042	0.019	-0.031	-0.006	0.010	0.037	-0.018
November	-0.046	-0.023	0.000	0.001	0.029*	-0.004	-0.008	-0.023	0.010	0.000
December	-0.005	-0.031	0.087*	0.005	0.106*	0.096*	0.068*	0.061*	0.020*	0.019
Crisis		-0.007		-0.116*		-0.032*		-0.052*		-0.063*

Variance

Constant	-3.287	-3.412	-5.307	-3.129	-4.812	-4.879	-6.476	-6.493	-7.789	-5.772
February	-0.488	-1.017	-0.266	2.696	-1.872	-1.521	0.218	-1.395	-0.377	-2.052
March	0.873	-0.139	-0.899	0.783	-2.851	-0.876	0.793	-0.405	-0.946	-1.460
April	-0.077	-0.028	-1.071	-0.512	-1.353	0.468	-0.622	-1.961	-1.568	0.152
May	0.270	0.296	-0.565	0.973*	-4.550	0.306	0.310	0.447	-0.291	-0.560
June	-1.505	-1.199	-2.749	-5.550	-1.900	-1.032	-1.277	-1.936	-0.757	-3.433
July	0.995	0.424	1.560	4.321	-3.182	-0.892	-0.415	-1.986	0.181	-0.120
August	0.858	1.179	-1.129	1.392	-2.153	-0.647	0.443	0.076	-0.859	-0.250
September	2.172	1.451	-0.649	-0.382	-2.248	1.274	1.642	0.239	1.011	-1.161
October	-0.928	-0.572	-0.298	1.064	-2.353	0.435	0.450	-0.558	0.226	1.594
November	0.709	0.185	-3.556	-1.210	-2.650	-0.659	-0.106	-0.946	-1.585	-2.936
December	1.728	0.829	-1.998	0.323	-6.036	-5.123	-0.730	-1.976	-3.230	-0.572
Crisis		1.645		0.337		2.138*		-0.329		-0.132
Va(ARCH)	-1.827*	-1.520	3.789	-0.979	3.203	-1.652	3.089	2.713	3.086	-0.981
Vd(Asymmetric)	-1.291	-1.247	-0.177	-2.643	0.758	-0.819*	0.305	-0.046*	-0.502	-2.399
Vb(GARCH)	-0.100	0.026	0.447	0.320	0.242	-0.020	0.379	0.205	0.111	-0.020
DOF	*285.207*	*192.677*	*144.734*	*138.832*	*301.440*	*108.872*	*170.427*	*78.161*	*125.185*	*55.848*
Log Likelihood	*30.790*	*34.248*	*57.841*	*71.748*	*74.722*	*78.943*	*74.781*	*81.568*	*89.782*	*110.907*

Table 6 reports the results analysed under the TGARCH model and it is noted that only BHLB and DEC1 exhibits some calendar effects being in January for BHLB and April and June for DEC1.Moreover,no volatility has been noted for any of the stocks.

TABLE 6
TGARCH Regression Results for Month of the Year Effect

	BBGI		BELFA		BHLB		DEC1		DEC10	
	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*	ϒ	ϒ*
Mean Equation:										
January	-0.066	0.011	-0.089	-0.070	-0.148*	0.150*	0.018	0.093	0.003	0.001
February	-0.042	0.057	-0.041	-0.012	-0.004	-0.008	0.015	0.021	0.010	0.013
March	0.079	0.091	-0.022	0.044	0.041	0.037	0.003	0.063	0.013	0.052
April	0.190	0.208	0.017	0.053	0.050	0.047	0.027	-0.069*	0.029*	0.058
May	-0.091	-0.079	-0.065	-0.042	-0.050	-0.052	-0.007	0.038	-0.015	0.010
June	-0.089*	-0.073	-0.005	0.014	-0.004	-0.004	-0.023	-0.002*	-0.042	-0.027
July	0.087	0.134	0.083	0.112	0.057*	0.056	-0.015	0.021	0.022	0.039
August	-0.123	-0.085	-0.032	-0.019	-0.040	-0.041	-0.033	0.012	-0.016	-0.000
September	-0.081	-0.025	-0.001	0.032	0.017	0.015	-0.025	-0.006	-0.010	-0.000
October	-0.055	-0.022	-0.013	-0.009	-0.033	-0.033	-0.028	-0.024	-0.011	-0.005
November	-0.122	-0.025	0.000	-0.004	0.015	0.012	-0.031	-0.040	0.022	0.010
December	0.208	0.181	0.073*	0.078	0.091*	0.089	0.038	0.046	0.029	0.037
Crisis		-0.112		-0.075		0.007		-0.066*		-0.049*
Variance Equation:										
Constant	0.045	0.043	0.017	0.016	0.004	0.004	0.004	0.003	0.002	0.002
February	-0.055	-0.075	0.020	0.012	-0.001	-0.001	-0.007	-0.003	-0.003	-0.001
March	0.019	0.015	-0.028	-0.012	-0.003	-0.003	-0.001	-0.000	-0.002	-0.000
April	-0.054	-0.047	-0.019	-0.023	-0.004	-0.004	-0.005	-0.002	-0.003	-0.001
May	-0.043	-0.045	-0.007	-0.007	-0.004	-0.004	-0.001	-0.000	-0.000	-0.000
June	-0.055	-0.051	-0.019	-0.021	-0.003	-0.003	-0.006	-0.005	-0.002	-0.003

July	-0.028	-0.040	0.004	-0.000	-0.003	-0.003	-0.004	-0.003	-0.001	-0.000
August	0.004	0.001	-0.019	-0.014	-0.003	-0.003	-0.002	0.001	-0.002	-0.000
September	0.004	-0.006	-0.018	-0.015	0.002	0.002	0.005	-0.000	0.003	0.001
October	-0.082	-0.077	-0.001	-0.009	-0.002	-0.001	-0.007	-0.002	0.000	0.001
November	-0.005	-0.040	-0.025	-0.020	-0.005	-0.006	-0.007	-0.004	-0.005	-0.004
December	0.016	0.022	-0.016	-0.015	-0.006	-0.006	-0.003	-0.003	-0.003	-0.002
Crisis		0.009		-0.000		0.000		-0.000		-0.000
Va(ARCH)	0.032	0.034	0.077	0.061	0.065	0.070	0.304	0.096	0.057	0.011
Vd(Asymmetric)	0.022	0.164	0.158	0.084	-0.127	-0.130*	0.155	-0.058*	0.255	0.056
Vb(GARCH)	0.518	0.525	0.426*	0.511	0.552	0.550	0.536	0.519	0.561	0.525
DOF	*45.173*	*33.871*	*37.743*	*20.739*	*20.432*	*20.378*	*23.771*	*20.168*	*125.185*	*20.477*
Log Likelihood	*11.777*	*17.379*	*44.038*	*42.171*	*74.007*	*72.278*	*79.907*	*70.738*	*89.782*	*83.323*

*DOF-Degree of Freedom. * = significant at the 5% level.*

5. Summary and Conclusion

The aim of the study is to investigate whether stocks follow a random walk. With the aid of autocorrelation testing, variance ratio tests and calendar effects testing, made under OLS regression as well as the GARCH family models, two indices, DEC1 and DEC10, and three individual stocks, BBGI, BELFA and BHLB, were tested.

Confirmed under both a daily perspective as well as on a monthly one, the returns of BBGI and DEC10 have demonstrated to follow a random walk while DEC1 and BHLB have shown the contrary. It supported a day-of-the-week effect as well as a month-of-the-year effect. BELFA provided evidences that it does not follow a random walk when tested using daily data but these effects vanished under a monthly perspective.

DEC1 has reported positive return of around 0.1% on Mondays and up to 9.4% during January. Moreover, a negative return up to 9.4% has been found during April decreasing to 4.7% during June. Even BHLB has shown positive Monday return around 0.18% and positive January return up to 14.9%. Negative trends of its returns were discovered on Fridays and around June being up to 3.6%. Both DEC1 and BHLB (being the financial industry) may have exhibited such trend due to the crisis where fear and lack of confidence among investors were governing the market.

However, the results-will help investors earning abnormal profits by devising a trading rule to exploit those detected anomalies. Nevertheless, several reasons may cause an investor not successfully reap profits from exploiting these calendar effects. Firstly, transaction costs might be more than the potential gain and thus making the transaction not profitable especially if it is small. Secondly, there may be reasons external to market such as the timing of public announcement of interest rate changes which result in the uncertainty as to whether the calendar effects will materialize.

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