*Original Article*

# Stock Returns and Long-range Dependence

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**Abstract**

This article studies the long memory behaviour of stock returns on the Ghana Stock Exchange. The estimates employed are based on the daily closing prices of seven stocks on the Ghana Stock Exchange. The results of the autoregressive fractionally integrated moving average-fractionally integrated generalized autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH) model suggest that the stock returns are characterized by a predictable component; this demonstrates a complete departure from the efficient market hypothesis suggesting that relevant market information was only partially reflected in the changes in stock prices. This pattern of time dependence in stock returns may allow for past information to be used to improve the predictability of future returns.

**Keywords**

ARFIMA, FIGARCH, GSE, long memory, stock returns

## Introduction

The long memory processes can be outlined as a physical science in the assessment of data. Hurst (1951) introduced formal models with long memory that relate to investigating the nonperiodic cycles by hydrological studies, which is associated with the normal flow of the Nile River. The long memory process is mainly centred on the clarification in the past that is extremely linked with explanation in the future. In other words, the long-range dependence can be expressed as long memory; thus, the present value depends on the previous value. The global market efficiency has been directly affected in the stock market returns by the presence or absence of stochastic long memory and this phenomenon can pose a severe challenge to the proponents of random walk behaviour of the stock returns.

This behaviour has an imperative repercussion for asset pricing models, fund managers, and economic development as a whole. In light of the interest generated by these market participants, trading strategies

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may vary when proceeds are branded by a positive autocorrelation above negative autocorrelation and short horizon above the long horizon.

The absence or presence of knowledge in the long memory properties of stock prices enables investors to make informed decisions about their investment portfolios. This also goes a long way in making the stock market more efficient since all information about the market is open to all investors. An investor in the above instance, will spend more in stocks with a risk aversion relatively better than unity or if returns will be successively independent in any long investment horizon.

The reminder of the article covers: the second section describes the development of the Ghana Stock Exchange. The third section covers the details of the autoregressive fractionally integrated moving average-fractionally integrated generalized autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH) modelling technique used in the study. The fourth section presents the results and discussion. The last section contains the conclusion and policy recommendations.

## Literature Review

Long memory process in the volatility of prices is considered to be a stylized fact in finance. It is well known that asset returns contain insignificant serial correlation in agreement with the efficient markets hypothesis although its volatilities exhibit significant autocorrelation. Currently, there is considerable evidence from other financial markets in support of the stock prices stochastic volatility in long memory and these are well documented in several studies (Andersen & Bollerslev, 1997, 1998; Breidt, Crato, & Lima, 1998; Ding, Granger, & Engle, 1993). According to Harvey (1993), he acknowledged the long memory volatility of stock prices. His findings initiated research into possible explanations and development of different models for volatility, like FIGARCH), which serves as the current technique for measuring stock price volatility due to the deficiencies of rescaled range model.

In a recent study, Singh and Chakraborty (2017) examined the evolving market efficiency of India ADRs, the underlying stocks, and the representative indices of the United States and the Indian stock markets, the emerging market of India. The study showed that an increasing market efficiency was prevalent over time.

Similarly, Robinson and Bangwayo-Skeete (2017) conducted a study that investigated the reaction of stock prices to major national news, which did not exclude credit rating reviews, international news, natural disasters, and the parliamentary elections. Their findings show that low levels of trading activity may be associated with semistrong form market inefficiency. The implication is that stock prices on relatively inactive markets may not fully reflect all relevant publicly available information.

Mandelbrot (1971) 'first studied the financial market on impact of long memory and he examined whether security returns exhibit long memory subsequently, probability that any current information from the market can never be arbitraged away, which presuppose arbitrage cannot imitated in security returns with martingale technique'. 'Additionally, the arbitrage pricing theory on the standard tests was analysed and long memory showed in asset prices led to the dismissal of capital asset pricing model' (Lo, 1991). Ghana as a developing economy has not taken full advantage of the domestic stock market. The research work seeks to test the efficiency of the Ghana Stock Exchange to ascertain how information today affects the returns on stock.

Not many researchers have applied ARFIMA and FIGARCH models in their works on the efficiency of the Ghana Stock Exchange. Although Tweneboah, Amanfo, and Kumah (2013) applied ARFIMA and FIGARCH in their article, they scrutinized the long memory behaviour of real interest rates in Ghana.

On the contrary, this study examines the efficiency of the Ghana Stock Exchange with a prime interest in the post automation of the market from 2010 to 2014 after Mensah, Pomaa-Berko, and Adom (2014). This study will enhance a decisive assessment of the degree of the weak form efficiency of the listed stocks and the market index. This will be significant because investors and traders want to know how shocks influence volatility and the role that structural adjustments can play in this development.

## Historical Development of the Ghana Stock Exchange

The launch of the Ghana Stock Exchange in 1990 was preceded by a punctilious financial reform with the ultimate goal of aggrandizing financial liberalization. This new phenomenon to some extent encouraged some foreign investors to participate in the domestic capital market of Ghana. In total, 21 firms were listed in 1996, with capitalization of USD 1.5 billion.

After 11 years of the establishment of the Ghana Stock Exchange, the market capitalization improved to USD 2.4 billion with the number of firms increasing to 32. In spite of this august development, liquidity was still low as 3.4 per cent match up to 1.1 per cent as recorded 10 before. The stock market witnessed about 12 per cent growth in total assets of listed firms between 1995 and 2002. The domestic stock market has a significant role in financing the expansion of firms in Ghana (Yartey & Adjasi, 2007). The Ghana Stock Exchange becomes infinitesimal and illiquid when it is compared to the volumes of trade on the New York Stock Exchange and the London Stock Exchange even though it has been a vital source of financing for firms in Ghana.

## Model Specification and Methodology

In this section, the researchers described the methodology that was used to achieve the objectives of the study. The ARFIMA and FIGARCH models are described in detail.

### *Fractional Integration Models*

The usual technique designed to analyze the integration property of a series is the unit root and cointegration tests. Such tests show the difference between the $I(1)$ and $I(0)$ data generating processes. There exists a vast literature on cointegration tests and the unit root used in stock return, which is measured by the time series properties (Neely & Rapach, 2008). However, cointegration tests and unit root experience the ill effects of low power, when the genuine model is constant. Likewise, the tests are excessively restrictive and do not tell much concerning the true behaviour of variables with the exception of charactering it as $I(0)$ or $I(1)$.

Accordingly, investigations into the fractional integration of the ex ante and ex post stock return (Granger, 1980; Granger & Joyeux, 1980; Hosking, 1981). $I(d)$, $0 \leq d \leq 1$ is the fractionally integrated series. At the point where $d = 1$, the series is $I(1)$, with shocks having infinite memory or lasting impacts. Where $d = 0$, the series is $I(0)$, and shocks out to exist at a geometric rate. An intermediate incident happens where $0 < d < 1$: The series is mean-reverting, as in the $I(0)$ case, yet shocks now vanish at a much slower hyperbolic (instead of geometric) rate. Series in which $0 < d < 1$ display 'long memory', mean-reverting behaviour, and can be significantly more persistent more to an exceptionally persistent $I(0)$ series.

Volatility have a tendency to transform gradually after some period and as appeared in Granger, Engle, and Ding (1993) amid others, the impacts of a shock may take a significant period to perish. Hence, the difference amongst unit root and stationary processes is by all accounts extremely restrictive. To be sure, exponential rate of decay can be linked to the propagation of shock in a stationary process (so that it just exhibits short-memory), whereas for a unit root process, the persistence of shocks is endless. The ARFIMA specification is planned to bridge the gap between complete and short persistence in the contingent mean, in order for the short-run behaviour of the time-series to be showed by the ARMA parameters, whereas the fractional differencing parameter takes into account displaying the long-run dependence.

## *ARFIMA Model*

Keeping in mind the end goal to show the long memory in stock prices, the ARFIMA (*m*, *d*, *n*) technique created by Hosking (1981) and Granger and Joyeux (1980) is utilized. As already elaborated, this model has been widely employed to investigate the financial time series behaviour. The technique is communicated as:

$$\phi(L)(1 - L)^d Y_t = \theta(L)\varepsilon_t \tag{1}$$

$L$ denote the usual lag operator, $\phi(L)$ and $\theta(L)$ are the $q$th and $p$th degree polynomials in that order, and defined as $\phi(L) = 1 - \sum_{j=1}^{p} \phi_j L^j$ and $\theta(L) = 1 + \sum_{j=1}^{q} \theta_j L^j$. $d$ is the differencing parameter, which can be a fractional number, the roots of $\phi(L)$ and $\theta(L)$ be positioned outside the innovation sequence and the unit circle, $\varepsilon_t$ is zero mean with a white noise and variance, $\sigma^2$.

## *FIGARCH Model*

ARFIMA representation in squared errors ($\varepsilon^2$), which is the expansion of the FIGARCH (*p*, *d*, *q*) technique of Baillie, Bollerslev, and Mikkelsen (1996). Generally, demonstrating to this technique may be deduced after the standard GARCH process is expressed as below:

$$\phi(L)(1 - L)^{\bar{d}} \varepsilon^2 = \omega + [1 - \beta(L)]\upsilon_t \tag{2.a}$$

$\varepsilon_t^2$ is the squared error of the GARCH process, $\upsilon_t = \varepsilon_t^2 - \sigma_t^2$ is mean zero serially uncorrelated error. $\{\upsilon_t\}$ Process is integrated to be the 'innovations' for the conditional variance $\sigma_t^2$. If $\bar{d} = 1$, the FIGARCH process turns out to be an included GARCH process. If $\bar{d} = 0$, the FIGARCH (*p*, *d*, *q*) process trims down to a GARCH (*p*, *q*) process. Reorganizing the expressions in Equation (2.a) above, FIGARCH technique may be restated as below:

$$[1 - \beta(L)\sigma_t^2 = \omega + [1 - \beta(L)(1 - L)^{\bar{d}}]\varepsilon_t^2 \tag{2.b}$$

The conditional variance equation of $\varepsilon_t^2$ is computed as

$$\sigma_t^2 = \frac{\omega}{[1-\beta(\mathrm{L})]} + [1 - \frac{\phi(L)}{[1-\beta(L)}(1-L)^{\bar{d}}]\varepsilon_t^2 \quad (2.c)$$

That is,

$$\sigma_t^2 = \frac{\omega}{[1-\beta(1)]} + \lambda(L)\varepsilon_t^2 \quad (2.d)$$

where $\lambda(L) = \lambda_1 L + \lambda_2 L^2 ......$

Additionally, all the roots of $\phi(L)$ and $[1-\beta(L)]$ and $d \in (0, 1)$ lie down outside the unit circle. Other GARCH techniques are being captured by the FIGARCH ($p$, $\bar{d}$, $q$) techniques, which is equivalent to standard GARCH technique and the IGARCH process, where $\bar{d} = 1$ and $\bar{d} = 0$, in that order.

Whereas $\bar{d}$ confines long memory in the FIGARCH technique, its understanding is not the same to that reflected by the ARFIMA in the light of the fact that the FIGARCH process cannot be covariance stationary other than severely stationary and ergodic for $0 \leq \bar{d} \leq 1$ and consequently the unconditional variance of $\varepsilon_t$ cannot be shown (Baillie, 1996). Baillie et al. (1996) noticed that the effect of a shock on a conditional variance of FIGARCH ($p$, $d$, $q$) processes diminishes at a hyperbolic rate when $0 \leq \bar{d} \leq 1$. Therefore, traditional GARCH model parameters show the long-term dynamic, which is considered by the short dynamic and the fractional integrated parameter $d$.

## Results and Discussion

The goal is to showcase the visible time series elements of the stock prices and returns; the graphs of the individual series are presented in this section. Figure 1 shows the graphs of the natural logarithm of the price series. There is a specific upward pattern within the series especially in the price series from 2012, denoting increases in stock prices. Figure 2 also shows the graphs of the individual return series.

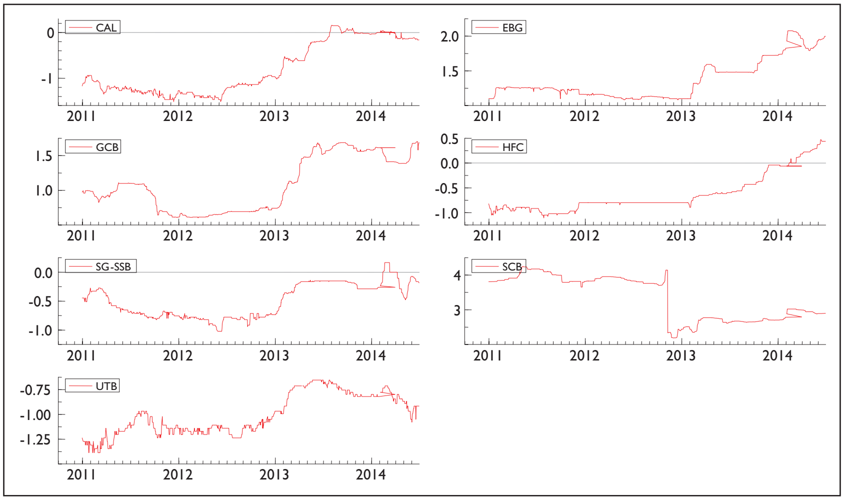


**Figure 1.** Graph of the Natural Logarithm of Stock Prices

**Source:** The authors.

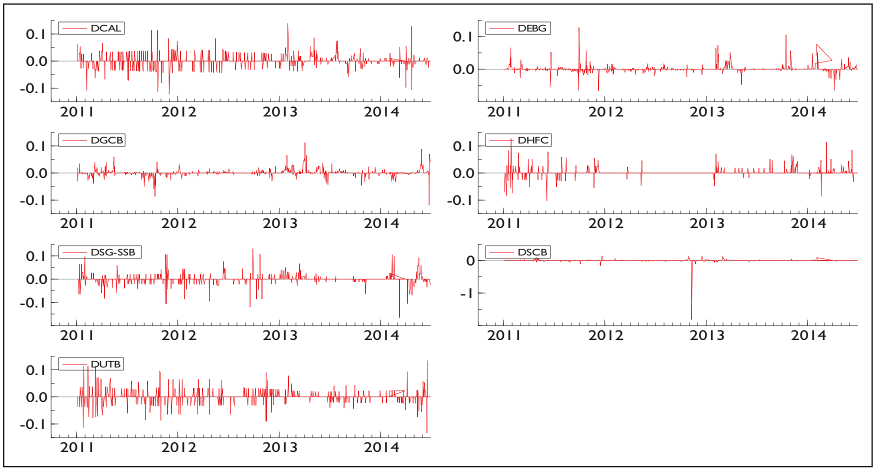


**Figure 2.** Graph of the Individual Return Series

**Source:** The authors.

## *Descriptive Statistics*

From the graphical analysis, the researchers present the properties of the series in Table 1. In terms of mean or average returns, all the variables have positive returns except UTB, which has negative returns. Quite interestingly, all the stocks have average returns of approximately 0.1 per cent. UTB has a moderately high standard deviation of 0.063, which demonstrates that the data points scatter or spread far or wide from the mean. All the series appear extremely non-normal. The returns distributions of SCB, UTB and SG-SSB are negatively skewed. Once more, all the returns distributions show a high level of excess kurtosis (leptokurtic). The negative skewness suggests a higher probability of expansive declines in market portfolio returns than increments, or substantial negative returns have a tendency to be bigger than the higher positive returns. Such skewness and kurtosis are basic elements in asset return distributions that are more than once observed to be leptokurtic. This behaviour shows that the returns have higher peaks than would be normal from typical distribution.

**Table 1.** Descriptive Statistics

| | Mean | Std. Dev. | Skewness | Kurtosis | Jarque–Bera |
|---|---|---|---|---|---|
| SCB | 0.001433 | 0.018125 | −0.180106 | 25.63035 | 18462.79* |
| CAL | 0.001166 | 0.022546 | 0.225264 | 10.98719 | 2306.603* |
| EGL | 0.001481 | 0.019500 | 0.955671 | 15.71166 | 5955.509* |
| GCB | 0.000827 | 0.012666 | 0.270443 | 28.40469 | 23271.78* |
| HFC | 0.001456 | 0.015241 | 1.225059 | 22.81868 | 14372.81* |
| UTB | −0.000881 | 0.062803 | −26.81215 | 766.2794 | 21101348* |
| SG-SSB | 0.000301 | 0.021175 | −0.306468 | 17.89739 | 8012.343* |

**Source:** The authors.

**Note:** *Indicates rejection at 1% significance level.

Convincingly, the Jarque-Bera test for the null hypothesis of normality is rejected for the returns series at the 1 per cent significance level. This recommends that all the variables deviate from the normal distribution. The Jarque–Bera analysis is a decency of-fit estimate away from normality, in view of the sample skewness and kurtosis, and is distributed as a chi-squared with two degrees of freedom. The null hypothesis is a combine theory of both the excess kurtosis and skewness. The $p$-value is smaller than the 1 per cent level of significance proposed to reject the null hypothesis. This demonstrates that the prices are not all around estimated by the normal distribution.

## *Estimate of Long Memory/Fractional Integration Parameter*

Although the unit root and variance ratio tests establish evidence of non-random walk processes, they cannot determine the degree of integration. The unit root tests only distinguish between $I(0)$ and $I(1)$ variables. In this segment, we show the findings of the long memory (fractional integration) analysis performed for each of the seven stock returns. The terms long memory, long-range dependence, strong dependence, or persistence can be used interchangeably. As stated earlier for each of these seven series, we report the estimates of both the GPH and the modified log-periodogram regression for each of the sectors included in Table 2.

Based on the GPH and RHE, the fractional differencing parameter estimates are statistically significant for SCB, EGL, GCB and SOGEGH, while the rest (CAL, HFC and UTB) are not statistically significant at the 1 per cent significance level. In terms of magnitude, whereas CAL has negative parameter estimate, the rest are positive. All the significant parameters are positive and have been concentrated between 0.002 and 0.156. These findings suggest that the returns series are generally mean-reverting, however, takes place at a very slow speed. The results of the GPH log periodogram estimates indicate that CAL is anti-persistent since it had negative differencing parameters albeit insignificant. HFC and UTB are positive but statistically insignificant. The remaining four (4) stock returns series (SCB, EGL, GCB and SG-SSB) are positive and statistically significant at 1 per cent level. The differencing parameter is either 0.1 or 0.2.

According to the Robinson and Henry's Gaussian semiparametric estimates, CAL, HFC and UTB are again not statistically significant since they have $p$-values greater than the preferred significance level. However, the remaining four (4) stock returns series (SCB, EGL, GCB and SG-SSB) are statistically significant at 1 per cent level.

## *ARFIMA (p, d, q) Models*

The parametric estimation for the returns series were derived by means of the exact maximum likelihood estimation (MLE) of the OxMetrics 6 ARFIMA package, while the Time Series Model (TSM hereafter) was used to obtain the long memory estimates via semiparametric methods. The ARFIMA model's Exact MLE in the OxMetrics 6 package was used (see Doornik & Ooms, 2003). The techniques with different orders are analyzed for ARFIMA ($p$, $d$, $q$).

The fractional differencing parameter, $d$, which is the size of the mean equation, is considered by examining market efficiency. Table 2 shows the predominance of long memory in prices on the Ghana Stock Exchange. All the stocks measured in this study show evidence of long memory. The fractional differencing parameter estimates are determined somewhere around 0.013–0.856.

**Table 2.** Long Memory/Fractional Integration Tests

| | GPH | RHE | ARFIMA | FIGARCH |
|---|---|---|---|---|
| **SCB** | 0.135* | 0.092* | 0.180* | 0.102* |
| | [0.000] | [0.000] | [0.000] | [0.000] |
| **CAL** | –0.002 | 0.020 | 0.013** | 0.556* |
| | [0.959] | [0.399] | [0.033] | [0.000] |
| **EGL** | 0.156* | 0.122* | 0.392* | 0.268** |
| | [0.000] | [0.000] | [0.000] | [0.013] |
| **GCB** | 0.204* | 0.181* | 0.286** | 0.465* |
| | [0.000] | [0.000] | [0.022] | [0.000] |
| **HFC** | 0.026 | 0.032 | 0.166** | 0.719** |
| | [0.461] | [0.186] | [0.021] | [0.016] |
| **UTB** | 0.002 | 0.014 | 0.856* | 1.000* |
| | [0.965] | [0.554] | [0.000] | [0.000] |
| **SG-SSB** | 0.100* | 0.061** | 0.270** | 0.695* |
| | [0.000] | [0.011] | [0.041] | [0.000] |

**Source:** The authors.

**Notes:** Include intercept but no trend in unit root test, * and ** indicate rejection at 1% and 5% significance levels, respectively; GPH = log periodogram regression by Geweke and Porter-Hudak (1983); RHE = Gaussian semiparametric estimate by Robinson and Henry (1998).

The findings of the ARFIMA (1, *d*, 1) model initiated by Granger and Joyeux (1980) presented in Table 2 also signify that the long memory parameter is significant at the 5 per cent significance level for all the seven series. All the measurements are positive and range from 0.013 for CAL to 0.856 for UTB. The remained equities have the subsequent estimated d values: SCB (0.180), HFC (0.166), SOGEGH (0.270), GCB (0.286) and EGL (0.392). The results of the ARFIMA estimates point out that all the returns series have positive estimates that are statistically significant at the 5 per cent level. None is anti-persistent, and none is explosive. UTB is non-stationary. The FIGARCH component of the model incarcerates long memory in the conditional variance (volatility).

The differencing parameter, $d$ estimated by the FIGARCH component is also statistically significant at the 5 per cent level for all the variables. Again, none of the estimates is negative. The estimates range from 0.102 for SCB to 1.000 for UTB. The remaining estimates are EGL (0.268), GCB (0.465), CAL (0.556), SG-SSB (0.695) and HFC (0.719).

FIGARCH Model showed evidence of long memory in volatility among stocks. In the GSE, the discoveries to great extent validate the present of long memory in volatility except of CAL ($d = 0.556$), HFC ($d = 0.719$), UTB ($d = 1.000$) and SG-SSB ($d = 0.695$) where the outcomes acquired demonstrate that volatility cannot have a predictable element. SCB, EGL and GCB have a fractional differencing value of 0.102, 0.268 and 0.465 separately, which recommends a long memory element in volatility. At last, conditional variance equations, which show long memory parameters are essentially not quite the same as zero over all stocks studied in this research. The FIGARCH model exemplifies a positive limitation, which affects the validity of the estimated findings. Nonetheless, the outcomes from CAL, HFC, SG-SSB and UTB cannot fulfil the positivity restraint of the FIGARCH method; hence, findings from these stocks should be translated circumspectly. The critical size of $d$ and $d$ acquired from this equation represents the significance of modelling long memory in GSE. Moreover, the aftereffect of $d \neq 0$ from these techniques is rather different from our discoveries from the unit root tests that prompted a closure of $d = 0$. The estimates of the FIGARCH model suggest a generally statistically significant long memory parameter in the conditional variance of the returns series.

A handful of researchers have expressed worries about the efficiency of the Ghana Stock Exchange. Osei (2002) examined the reaction to yearly earnings announcements of the GSE. The findings showed that the GSE was inefficient with respect to the yearly earnings data discharged by the firms listed on the exchange. Frimpong (2008) additionally analyzed the weak form EMH of the GSE. The researcher concluded that the GSE is a typical example of a weak form EMH. In the work of Frimpong (2008) on GSE, the outcomes of the random walk and GARCH models collectively rejected the existence of random walk in the DSI day-by-day market returns. Besides, his tests for nonlinearity demonstrated the potency of the McLeod-Li and BDS model that the residuals of the market prices do not take after a random walk creating process. Hence, the nonappearance of random walk proves that the twists in asset pricing and risk show a characteristic inefficiency in the market. This suggests that a considerable measure of stock returns on the GSE are either underestimated or exaggerated as the market is for the most part inefficient. From the EMH, it will hence not be an exercise in futility for interested expert to examine the stocks.

## Conclusion and Policy Recommendations

The long memory properties of the Ghana Stock Exchange shown in this article studies as a standard for the weak form degree of the Efficient Market Hypothesis. It is vital on the premise that economic development in line with location of capacities is being influenced by handling data in efficient market. Besides, the results demonstrate the returns on most equity market in relation to volatility, which are examined, and it might suggest having risk management strategies and portfolio diversification. Specifically, financial speculators might find these outcomes valuable given that investment returns have a dynamic drive that is significant to price volatility, and the basic decider of risk premia in equity markets is likewise volatile.

The negative response or rejection to the weak form efficiency is reliable with past evidence, as well as hypothetically not amazing. The size of the GSE is similarly little and ruled by little capitalization stocks. Related high average exchange cost, for example, brings about restricted market activity and liquidity. By and by, these are just enticing instead of empirical contentions. It is conceded that evidence from somewhere else (Appiah-Kusi & Menyah, 2003) have illustrated that, for instance, weak form efficiency cannot be attributed to the size of a market. The rejection of the weak form efficiency is being clarified by the theoretical contentions, though not adequate. The rejection of the normality test depicts that the market is not efficient, which will lead to the prediction in the market that eventually makes investors take advantage of the market. Comparable finding was acquired by Frimpong (2008).

On the premise of this study, the researchers prescribe the investors should know in advance that in inefficient security exchange markets, substantial increases are pretty much as likely as overwhelming misfortunes. To ensure a safe flow of data to market applicants and enhance the efficiency of the market, there is a need for the GSE to be transformed. Furthermore, vital elements that are not making the market efficient can be linked to the few listed organizations and the span of market capitalization. Along these lines, singular investors should focus on stocks with greater exchanging activity and market capitalization. Besides, there has to be a decrease in exchange cost in order to enhance market exercises and, thus, liquidity.

GSE and the Securities and Exchange Commission (SEC) ought to undertake public training in stock exchange investment to help the expansion of the organizations listed on the GSE and support newly listed firms. Attempt ought to be made to get numerous firms listed on the stock exchange to improve competition. On the contrary, there can be inefficient markets for stocks in new companies, particularly for new companies in new industries that are not widely analyzed.

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