Does automation improve stock market efficiency in Ghana?

Justice Tei Mensah[a], Philip Kofi Adom[b] and Maame Pomaa-Berko[c]
[a]Department of Economics, Swedish University of Agricultural Sciences,
Box 7013, S-750 07 Uppsala, Sweden. Corresponding author:
Email: myjumens@gmail.com / justice.tei.mensah@slu.se;
[b]Department of Banking and Finance,
University of Professional Studies, Accra-Ghana
Email: adomonline@yahoo.co.uk;
[c]University of Ghana, mamapoms@yahoo.com

Abstract

The automation of the Ghana Stock Exchange (GSE) in 2008, among other reforms, was expected to improve the efficiency of the market. The extent of this truism has, however, not been empirically established for the GSE. In this study, we attempt to assess the impact of the automation on the efficiency of the GSE within the framework of the weak-form Efficient Market Hypothesis (EMH) based on the before and after approach. The study was done both at the aggregate and micro-level. The aggregate result showed that automation of the exchange did not improve the overall efficiency of the exchange. However, there is evidence that the number of market participants involved in the exchange has increased in the post-automation era. The results of the impact of the automation on the efficiency of the microstructure are, however, mixed. Generally, the rejection of the null hypothesis under homoscedasticity was found to be robust to heteroscedasticity for some firms, but the reverse was the case for other firms. This implies that the rejection of the null hypothesis under homoscedasticity is due to both heteroscedasticity and serial correlation. Based on the findings, a mix of strategies aimed at improving the efficiency of the exchange are recommended.

Keywords: automation, stock market efficiency, Ghana Stock Exchange

1 Introduction

One of the conspicuous trends in the global economy of the 20th century is the ease with which financial assets are transferred between economies, especially to developing countries (Alagidede, 2011). With high infrastructure deficits and hunger for growth, returns on investment in emerging economies are at all-time high. As a result, there are high capital inflows from developed economies to emerging markets, primarily in the form of foreign direct investments (FDIs) and equity investment. For instance, according to the World Bank (2006), in 2005 private capital inflows to emerging markets stood at $491 billion, up from $25 billion in 1990. These inflows were partly fueled by growth in the equity financing of publicly listed securities in emerging markets (Alagidede, 2011).

Given the myriad constraints associated with development assistance, which hitherto was a significant source of development finance in developing economies,

African Review of Economics and Finance Vol. 6, No. 1, June 2014 pp. 69–101

economic managers in these countries have gradually shifted their attention to private sector financing. The private sector offers another source of capital to governments without the often too stringent conditionalities associated with funding from sources such as Bretton Woods institutions (World Bank and IMF). Further, the contribution of financial markets to the growth of economies cannot be overemphasised as their development is essential for the mobilisation of domestic and international capital for both the private and public sectors (Alagidede, 2011). Thus, a well-functioning financial market is regarded as a *sine-qua-non* to the growth and development of emerging economies.

A key factor that influences the performance of stock (capital) markets and further realises their roles in diversifying risk, pricing and the allocation of capital, is the efficiency of the exchange. Market efficiency explains the degree to which share prices reflect all available and relevant information (Gupta & Basu, 2005), while the efficiency of the stock exchange ensures the accurate pricing of stocks, by avoiding the under- and over-valuation of stocks which encourage share buying. This is because when stocks are incorrectly priced, it deters potential investors from buying shares for fear of perverse pricing when they decide to sell, and this ultimately reduces the capital available to firms for growth. Market efficiency also ensures the efficient allocation of resources, in the sense that a firm's performance is reflected in its stock prices, which inform potential investors when to take optimal investment decisions.

Due to increasing globalisation and rapid technological advancement, coupled with the need to ensure efficiency, the world's stock markets have gradually become automated, moving away from the hitherto manual trading floors on which brokers match orders using an open outcry system (Jain, 2005). As a result, automation and trading speed are becoming increasingly important aspects of competition among financial markets as they reduce transaction costs, enable the more efficient allocation of securities among heterogeneous investors, improve risk-sharing and consumption smoothing, and ensure accuracy in stock pricing, as the information is duly incorporated into prices (Pastor & Stambaugh, 2003; Acharya & Pedersen, 2005; Hendershott & Moulton, 2011).

In 2008, the Ghana Stock Exchange (GSE) began a process of migrating to a fully automated electronic trading system, which was completed in the first quarter of 2009. This reform was premised on the belief that it would improve efficiency (both operational and informational), enhance liquidity and further make the exchange more competitive so as to attract issuers and investors (Bowers, 2008). Thus, after years of operating on an automated system, the questions that beckon are: Is the GSE weakly efficient? Has the migration of the exchange enhanced its efficiency?

The literature is replete with studies on stock market efficiency in both developed and emerging economies (see, for example: Mecagni and Sourial, 1999; Magnusson & Wydick, 2002; Olowe, 2002; Smith, Jefferis & Ryoo, 2002; Appiah-Kusi & Menyah, 2003; Simons & Laryea, 2005; Mollah, 2007; Smith, 2008; Frimpong, 2008; Okpara, 2010). Even though the automation of exchanges in emerging markets has been on the rise, little is known about the effects which transitioning from manual floor trading to automation have on efficiency. Particularly in the case of Ghana, the authors did not find any studies analysing the effect of the automation of the GSE on the efficiency of the exchange. In fact, studies on Ghana have thus far only focused on testing the efficiency of the exchange, either at the aggregate level (Osei, 1998 and 2002; Magnusson and Wydick, 2002; Frimpong, 2008) or at the micro level (Ntim *et al*., 2007). This study therefore attempts to fill the gap in the literature by investigating the efficiency effects of automation in an emerging market, such as the GSE. Evidence from this study will contribute to the extant literature on the efficiency of capital markets in emerging markets, and the effects of structural and institutional reforms (such as automation) on market efficiency. In addition, it will offer policymakers insight into the impact stock market automation has on the efficient functioning of the capital market.

This study complements the aggregate analysis of the stock market efficiency and automation with a microstructure analysis of the effects of automation on stock market efficiency. This angle provides the point of departure of this study from previous studies on the impact automation has on efficiency (see Freund & Pagano, 2000; Benouda & Mezzez, 2003; Debysingh & Watson, 2007) and on stock market efficiency in particular (see Mecagni & Sourial, 1999; Olowe, 2002; Magnusson & Wydick, 2002; Smith, Jefferis & Ryoo, 2002; Appiah-Kusi & Menyah, 2003; Simons & Laryea, 2005; Mollah, 2007; Smith, 2008; Frimpong, 2008; Okpara, 2010).

The rest of article is organised as follows: In section 2, we present an overview of automation, market development and the GSE. Section 3 reviews relevant literature on capital market efficiency. Section 4 presents a discussion on theoretical and empirical models, while section 5 presents a discussion of data type and results. Section 6 concludes the article with a summary of findings and policy implications.

2 Automation, market development and the GSE

After the financial turmoil in Ghana[1] between 1983 and 1988, the financial sector witnessed a myriad of reforms aimed at liberalising and opening up access to long-term capital for investments (Frimpong, 2008). In 1988, the government launched the Financial Sector Adjustment Program (FINSAP), aimed at restructuring the financial sector and fostering the creation of new institutions to revitalise the financial sector. This resulted, among other things, in the establishment of the GSE in July 1989. Trading commenced in 1990 with 11 listed companies and one government bond (Frimpong, 2008).

Today, the GSE is the principal capital market in Ghana and one of the best-performing exchanges in sub-Saharan Africa. Market capitalisation of the Ghana Stock exchange, since its inception, has increased tremendously. From GH¢ 6.4

1 The period between 1981-1986 marks one of the challenging moments in the economic history of Ghana as periods of economic malaise and instability led to the implementation of the Economic Recovery Program in April 1983 and subsequently, the Structural Adjustment Program in 1986.

million in 1990, market capitalisation of the exchange has witnessed a significant and persistent increase over the period to reach GH¢ 57 264.22 million in 2012 (GSE, 2012). As shown in Figure 1, market capitalisation took an upward trajectory between 2001 and 2012 (except for 2009, when it declined by 11% from GH¢ 17 895.10 million in 2008 to GH¢ 15 941.92 million). The decline was due to the global financial crisis, which was felt in Ghana in the fourth quarter of 2008, the rise in interest rates and the introduction of automation to the exchange.

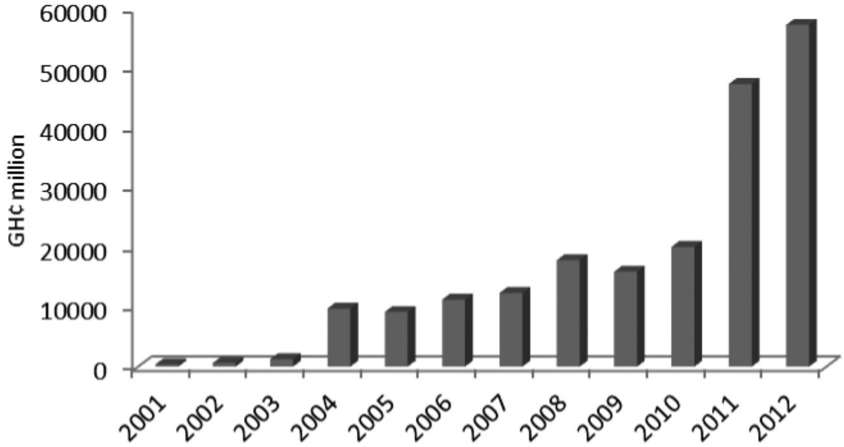

Figure 1: Trends in market capitalisation of the GSE (GH¢ million)

Source: Ghana Stock Exchange, market summary 2012.

An important observation from Figure 1 is that, between 2010 and 2012, market capitalisation more than doubled from GH¢ 20 116.70 million to GH¢ 57 264.22 million – a 184 per cent increase. This trend could be largely attributed to the listing of new companies such as Tullow Oil Plc in 2011. Overall, net of entry and exit, the number of listed companies on the exchange has increased steadily over the period, from 11 in 1990 to 34 in 2011 (see Figure 2).

In terms of the trading index, growth in the GSE All-share Index has also been impressive over the period under consideration. In 2008, for instance, the exchange witnessed one of the most outstanding performances of its listed equities, with a gain in the GSE All-share Index of 58 per cent. Consequently, the GSE was rated ahead of all the other African markets (GSE, 2009). The 2009 financial year was, however, difficult for the stock market, as the performance of the listed equities plummeted by 46.58 per cent in the GSE All-Share index from record levels in 2008 (GSE, 2009). As mentioned earlier, the dip in performance was deemed to be a corollary of the global financial crisis, which began to be felt in the fourth quarter of 2008, and the surge in domestic interest rates which made short-term financial instruments in the banking sector more attractive to investors than the stock market. The migration of the GSE from paper certification to electronic book entry securities under a new automated trading system, was viewed as another contributing factor, since any migration process requires time – investors, for instance, need to be convinced to come on board.

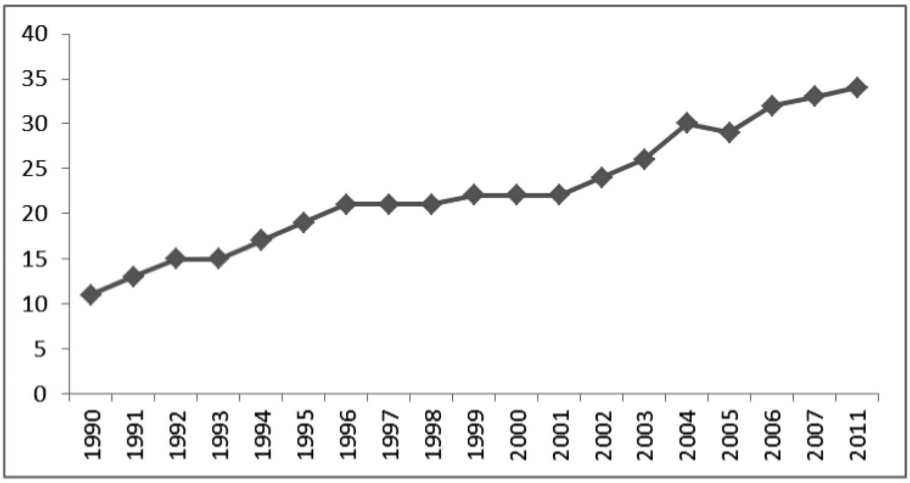

Figure 2: Trends in the number of listed companies on the GSE

Source: Ghana Stock Exchange, market summary 2012.

Given the success of the GSE, as among the best-performing exchanges in frontier markets, the market gradually became very attractive to both domestic and international investors. However, international best practice required that the GSE migrate from its hitherto manual listing towards a more efficient and digitised platform that would enhance and accommodate higher trading volumes, while improving efficiency. In this regard, the automation of the exchange became imperative. Thus, on 14 November 2008, the GSE embarked on a process of automation which was completed on 27 March 2009. Hence, the market was fully automated by the end of March 2009.

3 Literature review

The Efficient Market Hypothesis (EMH) is the most widely accepted model underlying the efficiency of capital markets. Formulated by Eugene Fama (1970), the EMH posits that a market is efficient when it adjusts instantaneously to take account of all available information, such that no single agent in the market obtains more information than what is already reflected in the market prices (Fama, 1970; Osei, 1998). Thus, with a given set of information, market efficiency results if it is impossible for any agent to make economic profits by trading on the basis of that information set (Ross, 1987), since all agents in the market are privy to the same information. In other words, stock markets are efficient if stock prices are random, such that it becomes impossible for any market participant to successfully execute a planned investment strategy that beats the market on a consistent basis. This implies that in an inefficient stock market, the presence of momentum in stock prices and anomalies (seasonal and day-of-the-week effects) enable market agents to accrue excess returns on their investments (Malkiel, 2007).

Fama (1970) outlined three main dimensions of capital market efficiency: weak-form, semi-strong and strong market efficiency, with each depending on the information set available. Weak-form market efficiency exists when current prices fully reflect all historical price information, such that prices automatically adjust to information changes without lags. Thus, excess gains cannot be made by studying the pattern of past price changes (Malkiel, 2007). Weak-form efficiency is based on the random walk hypothesis, where future price changes are independent of price changes in the past (Malkiel, 2007), implying that price changes do not follow any systematic pattern over time (Osei, 1998). Semi-strong form efficiency, on the other hand, occurs when market prices reflect available public information (including company reports, annual earnings, stock splits and company public profits forecasts). Strong-form efficiency, however, occurs when prices reflect both public and private information about earnings, book values and investment opportunities, inter alia (Malkiel, 2007). Thus, strong-form efficiency requires that market prices fully incorporate even private information, such as a pending merger between certain firms, or technological changes (Osei, 1998). Under this form of efficiency, not even the experts (portfolio managers and analysts) would be able to beat any index traded on the stock market (Malkiel, 2007). Intuitively, it implies that all markets can be weakly efficient, but not all markets can exhibit the stronger forms of market efficiency (Frimpong, 2008). Nevertheless, weak-form efficiency is the most tested among the three hypotheses in the empirical literature on stock market efficiency.

Literature abounds on the efficiency of the stock markets across the various exchanges in the world (see Borges [2008] for an extensive review on stock market efficiency). Nonetheless, the majority of studies on stock market efficiency have focused on the behaviour of stock markets especially in developed economies, where the weak-form efficiency hypothesis has seldom been rejected (e.g., Kendall, 1953; Fama, 1970; Hendershott & Moulton, 2011). Borges (2008), who studied the efficiency of the stock market indexes of France, Germany, the UK, Greece, Portugal and Spain, found that the stock markets of France, Germany, the UK and Spain exhibit random walk behaviour, while those of Greece and Portugal exhibit inefficiency due to serial positive correlation. Even though some studies have witnessed the predictability of future price changes in these markets (Poterba & Summers, 1988; Hudson *et al.*, 1996), no evidence has arisn of profitable trading strategies based on that predictability. Hence, developed financial markets as a whole have proved to be weak-form efficient.

A number of studies have attempted investigations into the efficiency of African markets, and particularly either single markets (e.g., Samuels & Yacout, 1981; Ayadi, 1984; Parkinson, 1984; Dickinson & Muragu, 1994; Osei, 1998; Olowe, 1999; Mecagni & Sourial, 1999; Asal, 2000; Dewotor & Gborglah, 2004; Ntim *et al*., 2007, Frimpong 2008) or multiple markets (e.g., Claessens *et al.*, 1995; Magnusson & Wydick, 2002; Smith *et al*., 2002; Appiah-Kusi & Menya, 2003; Simons and Laryea, 2004; Jefferis and Smith, 2005; Enisan and Oufisayo, 2009; Alagidede & Panagiotidis, 2009; Alagidede, 2011). Interestingly, the evidence from these studies varies and is even sometimes contradictory. For instance, whereas results from studies such as Magnusson and Wydick (2002) and Appiah-Kusi and Menyah (2003) suggest that the Johannesburg Stock Exchange in South Africa is weakly inefficient, the findings of Smith *et al*. (2002), Smith (2008) and Jefferis and Smith (2005) suggest otherwise. Specifically, using monthly data on Standard & Poor/ International Finance Cooperation (S&P/IFC) indices for various periods ending in 1998, to examine the efficiency of eight selected African exchanges?, Magnusson and Wydick (2002) discovered that none of the markets examined followed an i.i.d? random walk (hence they were weakly inefficient). However, index returns in local currency for four markets (South Africa, Côte d'Ivoire, Kenya and Mauritius) formed a martingale difference sequence (mds), whereas the remaining four markets (Botswana, Ghana, Nigeria and Zimbabwe) did not. On the other hand, using a joint variance ratio tests with weekly data on eight composite stock price indices over the period spanning January 1990 to August 1998, Smith *et al*. (2002) observed that the South African stock market is weakly efficient, whereas the markets of Botswana, Egypt, Kenya, Mauritius, Morocco, Nigeria and Zimbabwe failed to show any signs of efficiency. With regard to these varying conclusions, Smith (2008) argues that the differences emanate from the choice of estimation technique and the frequency of the data.

One compelling study on the African markets is by Jefferis and Smith (2005), who provide a time-varying analysis of weak-form efficiency in seven African markets (Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa and Zimbabwe) using the GARCH approach over the period 1990–2001. Their results revealed that whereas the JSE Securities Exchange was weak-form efficient during the period, the markets in Egypt, Morocco and Nigeria became weak-form efficient only towards the end of the period. Further, they showed that the Mauritius market exhibited a slow tendency to eliminate inefficiency, whiles Kenya and Zimbabwe showed no tendency towards efficiency.

In Ghana, research by Ntim *et al*. (2007), Frimpong (2008) and Osei (1998, 2002) is notable. Frimpong (2008) and Osei (1998, 2002) examined the efficiency of the GSE using a composite market index. However, Ntim *et al*. (2007) complement the literature with an analysis of the microstructure, by examining the efficiency of the individual stocks listed on the exchange. These studies unequivocally concluded that the GSE is weakly inefficient.

Finally, one would expect that studies on emerging markets (especially in Africa, where the majority were manually listed until recently), would attempt to ascertain the impact which migrating towards electronic listing would have on the efficiency levels of these exchanges. However, such empirical works are scant. Studies by Freund and Pagano (2000), Debysingh and Watson (2007) and Benouda and Mezzez (2003) are notable. Using nonparametric statistical analysis, Freund and Pagano (2000) measured the degree of market efficiency before and after automation at the New York and Toronto Stock Exchanges. Their findings indicate that the level of informational efficiency in these exchanges remained effectively unchanged during the automation period. Their results further indicated that automation in these exchanges coincided with an improvement in market efficiency at the Toronto Stock Exchange, relative to the New York Stock Exchange. Also, Debysingh and Watson (2007), using both parametric and non-parametric approaches, observed that the Trinidad and Tobago (TTSE) stock exchanges were highly inefficient during both the pre- and post-automation periods, albeit with some improvement later. Further, Benouda and Mezzez (2003) found that the automation of the Tunisian Stock Exchange (TSE) resulted in improved shares liquidity and decreased returns, but it did not have a significant effect on volatility or efficiency. Thus, these studies conclude that automation improves the level of informational efficiency of the market.

4 Data and methodology

4.1 Data type and sources

This study employs daily stock price index data of the GSE, from 2006 to 2011. We split the sample into the pre- and post-automation periods, to capture the efficiency impact of electronic listing on the GSE. The period 14 November 2008 to 27 March 2009 is excluded from the analysis, as the GSE was then operating under both manual and automated listings. This implies that the pre-automation period is taken as the 684 trading days from 17 February 2006 to 13 November 2008, while the post-automation period is taken as the 684 trading days spanning from 30 March 2009 to 30 December 2011. Daily market returns on 11 listed equities over the same period were also utilised. All data used in this study were obtained from the GSE Research Department.

4.2 Theoretical framework

The stock market is efficient if the current stock market price fully incorporates all the available information about that stock market, such that current stock price is the best predictor of future prices. In other words, a stock market is efficient if the stock market price follows a random walk. This implies that no prospective investor can readily earn extra profit above the market profit, since information is fully reflected in the current price. The Efficient Market Hypothesis (Fama, 1970) expresses stock market efficiency as

$$E\left(P_{j,t+1} \mid \varphi_t\right) = P_{jt} + E\left(r_{j,t+1} \mid \varphi_t\right) P_{jt} \tag{1}$$

where E is the expectation value operator, P_{jt} is the price of the j stock at time t, $P_{j,t+1}$ is the price of the j stock at time t+1, $r_{j,t+1}$ is the change in the stock market price index (return), and ϕ_t is the information set operator. Equation 1 shows that the expected j stock price at time t+1 conditioned on the information available at time t is the sum of the j stock price at time t and the product of the expected return of the j^{th} stock at time t+1 conditioned on the information available at time t and the j stock market price at time t. Thus, equation 1 implies that in determining the equilibrium expected returns, the information set operator is fully exploited.

The underlying assumption that market equilibrium determination can be stated in terms of expected returns, conditioned on the information set available at the time, has an important implication. Thus, the possibility of engaging in a trading system where the expected profit is in excess of the equilibrium expected profit is ruled out. The mathematical exposition that iterates this process is given as

$$X_{j,t+1} = P_{j,t+1} - E\left(P_{j,t+1} \mid \varphi_t\right) \qquad (2)$$

where, $X_{j,t+1,}$ is the excess market value of the j stock at time t+1. Equation 2 shows that the excess market value of a stock is the difference between the actual observed stock market price at time t+1 and the expected stock market price at time t+1, conditioned on the information available at time t. Given that the expected stock market price at time t+1 conditioned on the information available is assumed to be zero, that is,

$$E\left(P_{j,t+1} \mid \varphi_t\right) = 0 \qquad (3)$$

The excess market value of the j stock at time t+1 is similar to the actual observed stock market price at time t+1. Therefore substituting equation 3 into equation 2 yields

$$X_{j,t+1} = P_{j,t+1} \qquad (4)$$

4.3 Econometric techniques for efficiency measurement

Various techniques have been employed in the literature to examine the weak-form efficiency hypothesis. These include the Runs test (Bradley, 1968), the LOMAC variance ratio test (Lo & Mackinlay, 1988), the Durbin Watson test, the Unit root test of randomness in the series, and the GARCH model, inter alia. In this study, we employ the unit root test of randomness of the series, the Variance Ratio test and the GARCH model (see Bollerslev, 1980; Engle, 1982) to test the efficiency of the exchange, prior to and post automation of the GSE.

4.4 Unit root test of random walk hypothesis

The random walk hypothesis requires that the price index series contain a unit root. Given a time series, $\{X_t\}_{t=1}^{T}$, the unit root test of the Random Walk Hypothesis

(RWH) corresponds to the test of $H_0 : \phi = 1$ against the alternative of $H_A : \phi \neq 1$, in the first-order autoregressive model

$$r_t = \mu + \varphi\ r_{t-1} + \varepsilon_t \tag{5}$$

where μ and ε_t refer to the unknown drift term and error term respectively. However, Gilmore and McManus (2003, p. 44) argue that 'unit root is a necessary but not sufficient condition for a random walk'. Vitali and Molah (2011) also stress that 'a unit root process may imply the presence of predictable elements, in this case predictable successive price changes or returns, which are not consistent with the RWH, where these returns should be unpredictable, i.e. independent. It follows that the non-stationarity hypothesis can be verified through unit root tests whereas the independence assumption through the use of other tests.' As a result, this article adopts the BDS test of Non-Linear Serial Independence by Brock *et al*., (1987) to supplement the results of the unit root test.

4.5 Variance ratio (VR) test of the random walk hypothesis

The VR test is used to test the hypothesis that a given time series or its difference follows a martingale difference sequence. Thus, the VR approach tests the RWH against stationary alternatives. The test exploits the fact that the variance of random walk increments is linear in all sampling intervals. Thus, the sample variance of the k-period return of the time series r_t, is k times the sample variance of the one-period return. The variance at lag k is given as the ratio of $\frac{1}{k}$ of the k-period return to the variance of the one-period return. Mathematically, this is expressed as

$$V(K) = \frac{\dfrac{Var(r_t + r_{t-1}, \ldots r_{t-k+1})}{K}}{Var(r_t)} = 1 + 2\sum_{i=1}^{k-1} \frac{(k-i)\rho_i}{k} \tag{6}$$

where ρ_i is the i[th] lag autocorrelation coefficient of $\{r_t\}$. The central idea of the VR test is that when returns are uncorrelated over time, we should have $Var(r_t + r_{t-1}, \ldots r_{t-k+1}) = K\ \mathrm{var}(r_t)$. This means that the variance of the return equals unity. In other words, the VR test is a specification test of $H_0 : \rho_1 = \ldots = \rho_k = 0$; i.e., returns are serially uncorrelated. The overlapping data are used in computing the variance of long-horizon returns. According to Lo and Mackinlay (1988), the use of the overlapping data potentially improves the power of the VR test. However, this approach makes it difficult to analyse the exact distribution of the VR test, which is often not known. In practice, an asymptotic distribution is used for conducting statistical inference on the VR test, for fixed K and the sample size T increasing to infinity. Lo and Mackinlay (1988) proposed the asymptotic distribution of VR(r, k) by assuming that k is fixed when T approaches infinity. They proved that if r_t is i.i.d, that is under the assumption of homoscedasticity, then under the null hypothesis of the unit variance the test statistic is given as

$$M_{1(k)} = \frac{VR(r;k)-1}{\varphi(k)^{\frac{1}{2}}} \tag{7}$$

where $\varphi(k) = \frac{2(2k-1)(k-1)}{3KT}$ i s the asymptotic variance.

To accommodate for conditional heteroscedasticity in the series, Lo and Mackinlay (1988) proposed the heteroscedasticity robust test statistic

$$M_{2(k)} = \frac{VR(r;k)-1}{\varphi^{*}(k)^{\frac{1}{2}}} \tag{8}$$

Where

$$\varphi^{*}(k) = \sum_{j=1}^{k-1}\left[\frac{2(k-j)}{k}\right]^{2}\delta(j),\quad \delta(j) = \left\{\sum_{t=j+1}^{T}(r_t-\hat{\mu})^2(r_{t-j}-\hat{\mu})^2\right\} / \left\{\left|\sum_{t=1}^{T}(r_t-\hat{\mu})^2\right|\right\}$$

4.6 GARCH (1, 1) Model

The ARCH models and the generalised ARCH models (GARCH) were introduced by Engle (1982) and Bollerslev (1980) respectively. These models are widely used in various branches of econometrics, especially in financial time series analysis. The models permit for a time variant conditional variance and nonlinearities in the data-generating mechanism. As noted by Brook and Burke (2003) the GARCH (1, 1) model is sufficient to capture all of the volatility clustering present in the data, as it is based on the fundamental premise that the forecasts of time-varying variance depend on the lagged variance of the asset. Based on the standard GARCH (1, 1) model specification, we specify the GARCH (1, 1) estimated in this work as follows:

$$r_t = w_1 + \gamma r_{t-1} + \zeta_t \tag{9}$$

$$\delta_t^2 = w_2 + \alpha\zeta_{t-1} + \beta\delta_{t-1}^2 \tag{10}$$

where equation (9) is the mean equation expressed as a function of previous return (r_{t-1}), which is the change in the stock price index, a mean, w_1, and an error term, ζ_t. Since δ_t^2 is the one-period ahead forecast variance conditioned on past information, equation (10) is called the conditional variance equation. This equation has three parts: the mean, w_2; news about volatility from the previous period, measured as the lag of the squared residual from the mean equation; ζ_{t-1} (the ARCH effect); and the last period's forecast variance; δ_{t-1}^2 (the GARCH effect).

The estimation of the ARCH models is based on the maximum likelihood estimation method under the assumption that the errors are conditionally normally distributed. The conditional variance equation is often interpreted in a financial context as where an agent or trader predicts this period's variance by forming a weighted average of a long-term average (constant term), the forecasted variance from the last period (the GARCH effect), and information about volatility observed in the previous period (the ARCH effect). If the asset return is unexpectedly large in either the upward or downward direction, then the trader will increase the estimate of the variance for the next period.

The autoregressive root which governs the persistence of volatility shocks is that the sum of alpha and beta should be less than one ($\alpha + \beta < 1$) an indication of the stock market efficiency. However, the case where $\alpha + \beta \approx 1$ or even $\alpha + \beta > 1$ is an indication of high volatility clustering, which is an indication of an inefficient stock market. Both α and β should be non-negative. Specifically, we estimate the above GARCH (1, 1) model for both the pre- and post-automation sample periods using the Bollerslev-Woldridge's Quasi-Maximum Likelihood Estimator (QMLE) assuming the Gaussian standard normal distribution.

4.7 Non-linearity test using BDS

A crucial assumption of the efficient market hypothesis is that agents on the market are rational. Thus, brokers are risk averse, make unbiased forecasts, and respond instantaneously to new information (Gandhi *et al.*, 2005). Thus, the assumption of rationality implies linearity in the data-generating process. However, emerging stock markets are characterised by market imperfections and this sometimes causes investors to behave irrationally: an indication of non-linear dependencies. Gandhi *et al.* (2005) assert that

> given that a significant number of traders in emerging markets may trade on the basis of imperfect information, share prices are likely to deviate from their equilibrium values. In addition, given the informational asymmetries and lack of reliable information, noise traders in emerging markets may also lean towards delaying their responses to new information, in order to determine informed traders' reaction, and then respond accordingly (Oskooe, 2012). The theory and empirical evidence of non-linearity in share price changes suggest that the i.i.d assumption is a prerequisite for an appropriate assessment of efficiency market hypothesis.

Therefore, this article also examines the non-linearity in the stock market returns using the BDS test.

The BDS test was originally developed to test the i.i.d assumption, albeit that others have used it as a model misspecification test. The BDS technique tests for the null hypothesis of independence and identical distribution (i.i.d) against the unknown alternative. Specifically, the test examines the underlying probability structure of a time series, searching for any kind of dependence. Let ε_t be a sequence of residuals of length T. Further, we define the embedded sub-vector as $\varepsilon_t^m = (\varepsilon_{t-1},....\varepsilon_{t-m+1})$ and t= 1,2...,T_{-m+1} where the choice of m, the embedded dimension, is subjective. Because the vectors are required to be of equal length, m-1 data points are lost in the process. The correlation integral, which is measured as the distance between points ε_t^m and ε_s^m within the m-dimensional space, is used to analyse the dependence of the series.

$$C(\gamma, m, T) = \frac{2}{Tm(Tm-1)} \sum_t I_\varepsilon\ (\varepsilon_t^m, \varepsilon_s^m \qquad (11)$$

where γ is the choice of the metric band; T_m=T-m+1; t and s range from 1 to T-m+1 and are restricted such that t<s; $I_\varepsilon(\varepsilon_t^m, V_s^m)$ is an indicator function which equals 1 if $\| \varepsilon_t^m - \varepsilon_s^m \| < \gamma$ where ||.|| is the sup norm over the sub vector, which is given as $\| \varepsilon \| = \max, < i \leq m \mid \varepsilon_i \mid$. The BDS statistic is given as

$BDS(\gamma, m, T) = \dfrac{T_m^{\frac{1}{2}}(c(\gamma, m, T) - c(\gamma, m, T)^m)}{\delta(\gamma, m)}$, where $\delta(\gamma, m)$ is the asymptotic standard deviation with $\delta^2(\gamma, m) = 4[4K^m + 2\sum_{j=1}^{m-1} K^{m-j}c^{2j} + (m-1)^2 c^{2m} - m^2 Kc^{2m-2}]$.

The BDS statistic is divided by the asymptotic standard deviation so that it is distributed asymptotic normal with mean zero and variance one, under the null of i.i.d $\varepsilon_{t's}$. In practice m is chosen over the range of 2 to 15 and γ to lie between 0.5 and 2 standard deviations of the time series to be tested (see Granger & Andersen, 1978; Hsich, 1989). This is because, for a given m, γ cannot be too small because $C(\gamma, m, T)$ will capture too few points, nor should γ be too large in order to prevent $C(\gamma, m, T)$ from involving too many data points (see Cromwell, Labys, &Terraza, 1994).

5 Empirical results and discussion

5.1 Descriptive statistics of the GSE returns

Table 1 shows the summary statistics for returns using the full sample, the pre-automation and the post-automation samples. The mean return is positive with a relatively higher standard deviation, which indicates that trading on the GSE is risky (Frimpong, 2008). The skewness of return is negative, which implies that there is a higher probability of large decreases in market portfolio returns than increases. Also, the distribution of returns is highly leptokurtic, which signals asymmetry in the distribution of the market returns and is consistent with the results of the Jarque-Bera test of normality, which shows that the distribution deviates from normality.

The descriptive statistics for both sub-samples reveal that the performance of the GSE slacked after the automation. As shown in Table 1, the mean return turned negative post-automation. Also, the corresponding standard deviation is high post-automation but pre-automation – an indication that trading risk increased post-automation. One must, however, be careful in stating that the automation of the GSE caused returns to fall. In as much as we acknowledge the lag effect of policy implementation, other developments such as the outbreak of a fire at the GSE during this period also played a crucial role. As a result, one should be careful of attributing the fall in returns during post-automation solely to the lag effects of automation. Further statistics show similar patterns. As displayed in Figure 3,[2] the Quantile-Quantile (Q-Q) plot for the pre-automation period is concave, confirming that the distribution of the GSE returns is positively skewed with a long right tail. On the other hand, the Q-Q plot of the GSE returns for the post-automation period is convex, which indicates that the distribution of the GSE returns is negatively skewed with a long left tail. For the post-automation period, the distribution is very close to a lognormal distribution.

Table 1: Descriptive statistics for returns on the GSE All-Share Index

Measures	Pre-automation	Post-automation	Full Period
Observations1	683	683	1457
Mean	0.001181	-0.000377	0.000283
Median	0.000137	9.86E-06	7.41E-05
Maximum	0.059186	0.048302	0.059186
Minimum	-0.019862	-0.087540	-0.087540
Std Dev.	0.004651	0.010774	0.008132
Skewness	6.520576	-1.041882	-0.743005
Kurtosis	65.28186	13.72070	23.81689
Jacque-Bera	115399.4	3399.350	26459.74
Probability	0.000000	0.000000	0.000000

The returns for the GSE during the pre-automation period are positively skewed, indicating a greater probability of large increases in the market portfolio returns than falls. On the other hand, returns in the post-automation period are negatively skewed, indicating a higher probability of large decreases in the market portfolio returns than increases. In other words, the returns in both periods can be described as asymmetric.

However, the distribution of returns in both periods is highly leptokurtic (peaked), which implies that the distributions are not normal. These results are consistent with the Jarque-Bera test of normality. It rejects the null hypothesis of normal distribution for both periods. Further tests for normality, as shown in Table 2, reject the null hypothesis of normality at the 1% significance level.

2 Figure 4 shows the distribution for the full sample.

Table 2: Empirical distribution test

Method	Post-automation	Post-automation	Full Period
Lillie Fors (D)	0.312***	0.18***	0.25***
Cramer-Von Mises (W2)	27.46***	8.31***	35.79***
Watson (V2)	26.71***	8.28***	35.78***
Anderson-Darling (A2)	149.36***	40.01***	171.4***

**** indicates significance at 1%.*

Rejecting the normality assumption has implications for the random walk model. If stock returns series follow a normal distribution, it implies that they exhibit a random walk process, and, therefore, the market is said to exhibit weak-form efficiency. Thus, given the results of the normality test it can be concluded that the market shows some level of weak-form inefficiency in all periods considered.

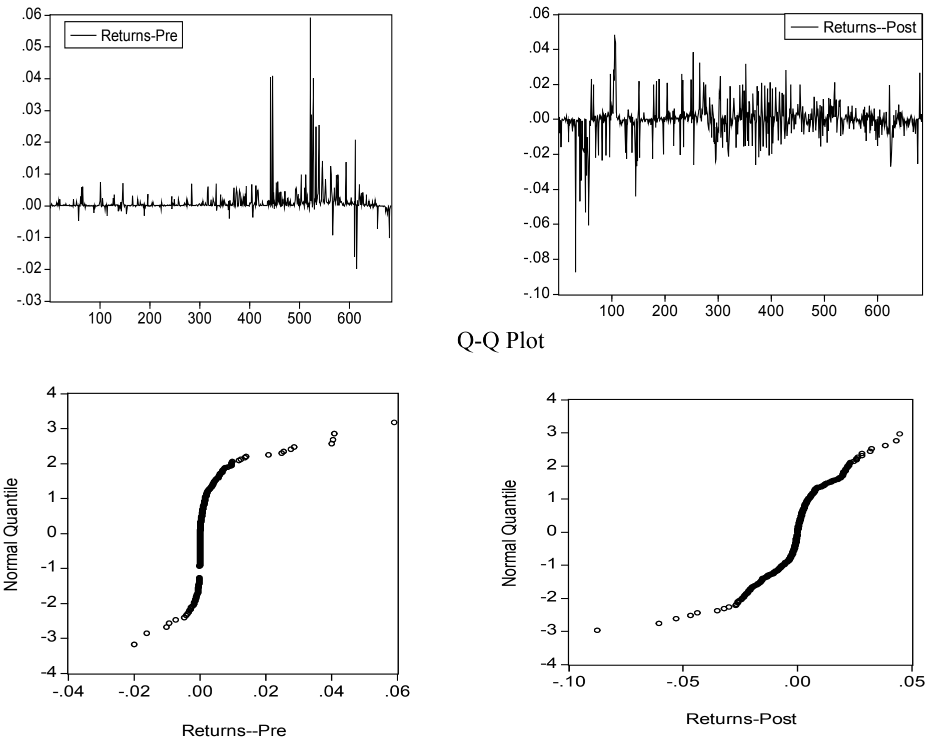

Figure 3: GSE returns and tail distribution (pre- and post-automation)

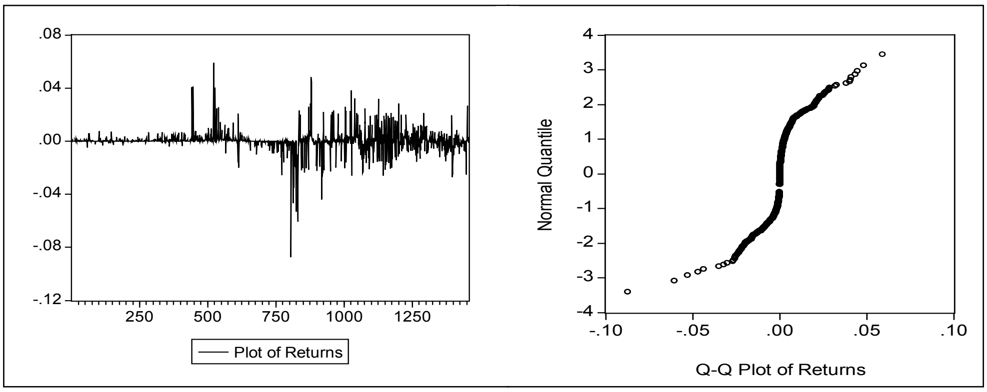

Figure 4: GSE returns and tail distribution for the entire period

5.2 Unit root test of the Weak-Form Efficiency Hypothesis

The Augmented Dickey Fuller test and the Phillip-Perron tests were used to test the RWH. The test was conducted for two cases: constant, and constant and linear trend. The results of the unit root tests (Table 3), in both cases considered, show that the stock market returns are stationary in levels across all periods. Thus, we reject the null hypothesis that the series contains a unit root at 1% significance level, i.e., that the stock return variable has a long history and that the moment conditions remain constant. This implies that, for both cases, the GSE market returns do not follow a random walk – an indication that the GSE exhibits weak-form inefficiency. Thus, the automation of the exchange has not significantly improved the efficiency of the capital market. This inefficiency implies that the market provides an opportunity for profitable arbitrage for market watchers, since returns can be accurately predicted using past information.

Table 3: Unit root test for GSE market returns

Model	Intercept		Trend and intercept	
Test	ADF	PP	ADF	PP
Pre-Automation	-5.922*	-27.648*	-6.131*	-27.147*
Post-Automation	-14.080*	-25.231*	-14.168*	-25.201*
Entire Period	-10.291*	-39.429*	-10.319*	-39.370*

* indicates 1% level of significance

5.3 Results of GARCH Model

A major limitation of the unit root approach to testing weak-form efficiency is that it fails to capture the degree of volatility clustering in the returns. Hence a more robust estimation technique is imperative. As a result, we estimate the GARCH (1, 1) model[3] which overcomes this limitation inherent in the unit root approach. The result[4] of the full-sample GARCH (1,1) model indicates that the AR(1) parameter in the mean equation is not statistically significant. This signals random walk, i.e, changes in current prices are attributed to random (noise) effects rather than previous prices. In other words, stock market returns based on the full-sample model follow a random walk process, which signifies the existence of weak-form efficiency. Similar results were obtained by Frimpong (2008).

However, the sum of the ARCH and GARCH effects in the variance equation show conflicting results. Weak-form efficiency requires the sum of the ARCH and GARCH effects to be less than unity and significant. However, the result shows that the combined ARCH and GARCH effects are very high[5] – a clear indication of persistent high volatility clustering and inefficiency on the exchange during these periods. Therefore, the GARCH (1,1) model provides inconclusive results on the efficiency of the market using the full-sample model. The news parameter (i.e., ARCH effects) is lower, but the persistence parameter is higher. This signifies that the rate at which news is impounded into prices is lower, while old news has a less persistent effect on price changes. The unconditional variance, measured as $\frac{w_2}{1-ARCH(1)-GARCH(1)}$ = -1.016, is negative an indication that the quantity of information flowing into the market is low.

An analogous result was obtained for the pre-automation sample. The autoregressive term in the mean equation is statistically insignificant, suggesting that the market prior to the introduction of automation was weakly efficient. However, the sum of the ARCH and GARCH effects is close to 1, which denotes higher persistent volatility clustering of the GSE exchange during this period. Given these results for the ARCH and GARCH effects, one can say that the GSE exhibited weak-form inefficiency prior to the introduction of the electronic listing. With regard to the post-automation period, the AR (1) parameter in the mean equation is statistically significant at 5% – an indication that current prices are determined largely by previous prices and thereby violate the random walk hypothesis. In other words, stock market returns in the post-automation period do not follow a random walk, and as a result, market participants can easily and accurately forecast future trends in market prices.

Therefore, the results suggest that the GSE, during the post-automation period, did not exhibit weak-form efficiency. This result is confirmed by the ARCH and GARCH effects in the variance equation, which are significant at 10% and 1% levels, respectively. The sum of the ARCH and GARCH effects is very high (0.88)

3 This model allows enables us to determine the level of volatility clustering in market returns, which has implications for efficiency levels.

4 See Table 4.

5 Approximately one.

and close to 1, which suggests high persistence of volatility clustering on the GSE market during the period. These results confirm that the GSE market during the post-automation period is (weakly) inefficient. The main conclusion, therefore, is that the automation of the GSE did not alter its efficiency. This is because the liquidity and efficiency of the GSE depend on rules pertaining to handling and executing trades, and, therefore, as long as these rules do not change, the efficiency and liquidity of the exchange are not expected to change.

However, further examination of the result reveals some positive impacts of the GSE automation. First, the news coefficient (i.e., ARCH effect) increased while the persistent parameter (i.e., GARCH effect) decreased post-automation. This implies that news is impounded into prices more rapidly, and old news has a less persistent effect on price changes post-automation. Also, the unconditional variance post-automation improved, which implies that the quantity of information flowing into the market increased. Intuitively, these results show that automation provides the most cost-efficient method of acquiring market exposure, compared to manual trading. As a result, there has been an increase in the number of participants involved in the market.

Table 4: GARCH (1, 1) Model for stock market returns

GARCH (1,1)	Pre-Automation	Post-Automation	Full Period
Mean Equation			
w_1	0.000233**	-6.52E-05	0.000214
AR(1)	0.044148	0.101398**	0.061789
Variance Equation			
w_2	1.61E-08***	1.30E-05	3.15E-08*
ARCH(1)	0.036469**	0.073117***	0.045797**
GARCH(1)	0.980558*	0.812700*	0.971067*

*, **, *** denote 1%, 5% and 10% respectively

The estimated GARCH variances and residuals for the periods are shown in Figures 5 and 6. The variance plot for the pre-automation period reveals unusually high persistent volatility for the latter part of the period, remaining relatively stable, however, for the most part of the period. There is the duration of time where the volatility is relatively high and relatively modest. The plot of the conditional variance for the post-automation period portrays a higher degree of volatility clustering for the first 100 observations, but the degree of volatility persistence moderates thereafter.

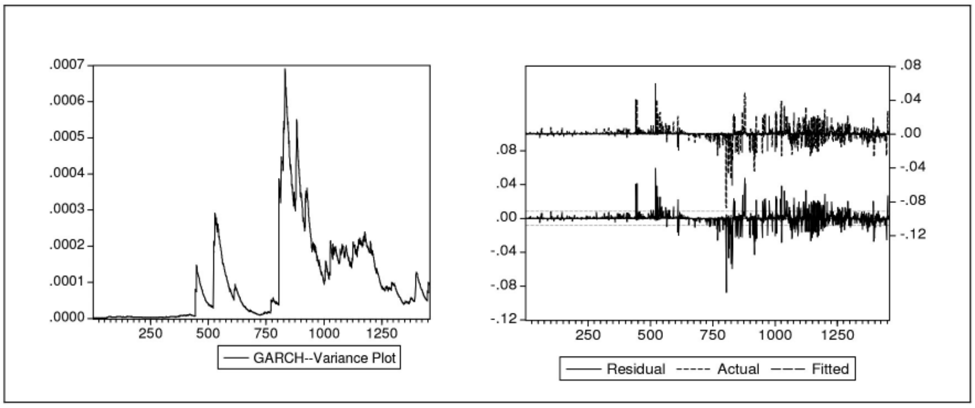

Figure 5: Plot of GARCH variance and residuals for the full sample period

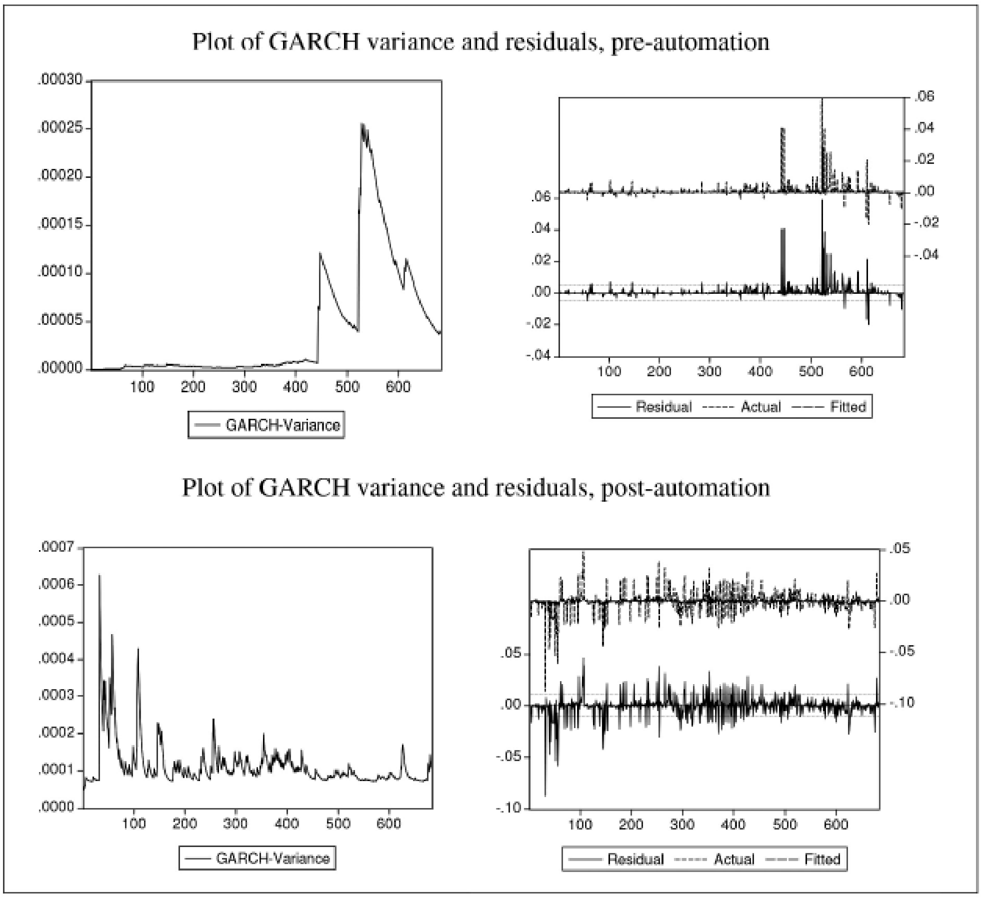

Figure 6: Plot of GARCH variance and residuals for the sub samples

5.4 BDS test for linear independence

To ascertain the true efficiency status of the exchange over this period, the analysis was further subjected to test of non-linearity using the BDS test of non-linear serial independence (see Table 4). The result of the BDS test shows that the statistics for all periods are statistically significant at the 1% level. Thus, we fail to accept the null hypothesis of serial independence for the GARCH model and, therefore, the residuals from the GARCH models for all periods are not identically independently distributed (i.i.d) – an indication of some hidden non-linear structure that drives the GSE returns series.

Table 5: BDS test of non-linear serial independence

Dimension	Pre-automation	Post-automation	Entire period
2	0.027543***	0.015426***	0.031254***
3	0.046444***	0.030004***	0.065038***
4	0.060275***	0.045470***	0.092098***
5	0.068008***	0.053533***	0.109877***
6	0.065970***	0.055137***	0.120008***

*** 1% significance level

In other words, the GSE returns in all three periods do not follow a random walk, and are hence inefficient. Thus, the evidence suggests that the introduction of automation to the operations of the GSE has not significantly improved its efficiency.

5.5 Tests for serial correlation, heteroscedasticity, and normality in residuals

The estimated GARCH models were also subjected to serial correlation, heteroscedasticity and normality in residuals tests. The correlogram of squared standardised residuals was used to test for the presence of serial correlation in residuals in the variance equation. The result (see appendix) indicates that the GARCH models estimated for all the periods (pre-, post-, and entire period) have no serial correlation in residuals of the variance equation. This suggests that the variance equation is correctly specified. The tests for heteroscedasticity and normality in residuals are shown in Table 6. From this table, it is obvious that the standardised residuals do not exhibit additional ARCH effect for all models, as is shown by the insignificance of the ARCH LM test. Also, the Jacque Bera test shows that the null hypothesis of normally distributed residuals cannot be accepted. This means that the histogram plots of the residuals are not bell-shaped.

Table 6: Test for heteroscedasticity and normality of residuals

TEST	Pre-automation	Post-automation	Full period
ARCH LM TEST: Heteroscedasticity	0.03296	0.00267	0.04240
	(0.8560)	(0.9588)	(0.8369)
Jacque Bera Test of normality	252362.6	8778.769	504295
	(0.0000)	(0.0000)	(0.0000)

Note: Figures in parentheses are probability values

5.6 VR test and the microstructure of the GSE

The conclusion of market inefficiency in respect of the GSE is more general and not significantly revealing. What is more revealing is to analyse the efficiency of the microstructure of the exchange.[6] As a result, we applied the LM (1988) variance ratio test for homoscedastic and heteroscedastic random walks over the three periods considered in the study. In all, 11 major equities[7] listed on the exchange were considered for 10-day, 15-day, 20-day and 25-day base observation intervals. As stated earlier, the LM variance ratio test reports the test statistics under the hypothesis that the returns follow a random walk.

The full sample model reveals that for five of the listed companies,[8] under the maintained hypothesis of homoscedasticity, the null hypothesis of random walk is rejected, implying that the variance ratios for these firms are significantly different from zero. Hence, these firms exhibit weak-form inefficiency. However, the hypothesis could not be rejected for the remaining six firms – an indication of weak-form efficiency in their market returns. Surprisingly, the results for ASI are rejected for only the first k interval. This inconclusive result confirms the results of the GARCH model. Similar results were obtained by Ntim *et al*. (2007) for the GSE. The general conclusion of the GSE market inefficiency vis-à-vis the heterogeneity of efficiency of the microstructure is a characteristic feature of a few dominant? firms on the exchange. Next, we split the sample accordingly to ascertain the impact of automation on the efficiency of the microstructure of the exchange. The test statistics for the pre-automation period, under the maintained hypothesis of homoscedasticity, show that for seven of the 11 equities, the null hypothesis of random walk is rejected, i.e., for seven of the eleven companies, the variance ratios are significantly different from one. The implication is that prior to the automation these seven equities were weak-form inefficient. However, for HFC, SWL and TBL, the null hypothesis of random walk, under the maintained hypothesis of homoscedasticity, cannot be

6 For the sake of brevity, descriptive statistics and plot of daily returns of the selected 11 equities are shown in the appendix.
7 These equities were selected randomly based on data availability.
8 ALW, BOPP, GCB, HFC, SWL

rejected at all trading days (k), which implies that the variance ratios for these firms are not significantly differently from zero. In other words, these three firms exhibited weak-form efficiency prior to the introduction of the automation.

During the post-automation period, the results show improved efficiency for only three equities. As shown in Table 9A, the null hypothesis of random walk is rejected for six equities, which implies that their variance ratios are significantly different from one: an indication of weak-form inefficiency. However, for five equities, the null hypothesis of random walk cannot be rejected – once again, an indication of the weak-form efficiency of these firms. Comparatively, it can be deduced that whereas the efficiency of AGA, GGBL and FML improved after the automation, SWL and TBL continued to exhibit weak-form efficiency in the post-automation era. Interestingly, HFC, which was weak-form efficient prior to automation became weak-form inefficient post-automation. However, for the remaining six equities, the automation of the exchange did not change the efficiency status. Because the above results were obtained under the maintained hypothesis of homoscedasticity, the rejection of the null hypothesis of random walk can either be attributed to heteroskedasticity or to autocorrelation.

For robustness, we complement the analysis with an estimation of the heteroscedasticity-consistent variance ratio test for all firms, for each of the four cases k=10, 15, 20 and 25. The results are shown in Tables 7B, 8B and 9B for the full sample, pre- and post-automation periods respectively. Based on the full sample, it is evident from Table 7B that the rejection of the null under homoscedasticity is robust to heteroscedasticity for BOPP, ALW, SWL and GCB. This suggests that these firms' variance ratios are different from one due to autocorrelation, rather than heteroscedasticity. The pre-automation result (see Table 8B) shows that the rejection of the null under homoscedasticity is robust to heteroscedasticity for ALW, BOPP, GCB, GGBL and HFC, which implies that, for these firms the variance ratios are different from one, due to autocorrelation. However, for FML and SCB, the rejection of the null under homoscedasticity is due to heteroscedasticity. Lastly, the results for the post-automation period (see Table 9B) reveal that the rejection of the null under homoscedasticity is robust to heteroscedasticity for ALW and SGSB, which implies that for these firms, the variance ratios are different from one due to autocorrelation. However, for five of the firms (AGA, GGBL, SCB, BOPP and HFC), the rejection of the null under homoscedasticity is not robust to heteroscedasticity. This means that the variance ratios for these firms are different from one due to heteroscedasticity. The general conclusion that can be drawn from the above is that the impact of automation on the efficiency of the microstructure of the exchange is mixed. The positive impact has been biased to only a few firms on the exchange. Similar patterns exist for the negative impact of the automation.

Table 7A: Homoscedasticity robust VR test for full sample period

K	AGA	ALW	BOPP	FML	GCB	GGBL	HFC	SCB	SGSSB	SWL	TBL	ASI
10	0.101	0.098*	0.112*	0.099	0.104*	0.101	0.102**	0.101	0.101	0.101**	0.101	0.108*
15	0.067	0.067*	0.079*	0.066	0.067*	0.068	0.067**	0.072	0.059	0.074**	0.091	0.074*
20	0.051	0.049*	0.054*	0.048	0.050*	0.051	0.050**	0.051	0.051	0.051**	0.051	0.058*
25	0.041	0.040*	0.047*	0.041	0.041*	0.041	0.041**	0.041	0.041	0.041**	0.041	0.042*

*, **, *** denote 1%, 5% and 10%, respectively

Table 7B: Heteroscedasticity robust VR test for the full sample

K	AGA	ALW	BOPP	FML	GCB	GGBL	HFC	SCB	SGSSB	SWL	TBL	ASI
10	1.006*	1.290**	1.764***	0.917	1.467**	1.043**	1.012	1.090**	1.012***	1.013***	1.014**	1.250*
15	1.009**	1.441**	1.970***	0.977	1.689***	1.059**	1.002	1.116**	1.019***	1.020***	1.019***	1.374*
20	1.013**	1.539**	2.127***	0.887	1.929***	1.070***	0.991	1.126**	1.083	0.819	0.971	1.476*
25	1.017**	1.617**	2.239***	0.729	2.086***	1.080***	0.995	1.129**	1.125	0.700	0.945	1.556*

Table 8A: Homoscedasticity robust VR test, pre-automation

K	AGA	ALW	BOPP	FML	GCB	GGBL	HFC	SCB	SGSSB	SWL	TBL	ASI
10	N/A	0.122**	0.103**	0.104*	0.116*	0.099**	0.069	0.098**	0.113*	0.102	0.102	0.109**
15	N/A	0.083**	0.068**	0.071*	0.072*	0.070**	0.047	0.071**	0.080*	0.069	0.069	0.072
20	N/A	0.062**	0.056**	0.052*	0.057*	0.051**	0.035	0.038**	0.059*	0.052	0.052	0.053
25	N/A	0.050**	0.048	0.044*	0.047*	0.043**	0.029	0.041**	0.050*	0.042	0.042	0.042

Table 8B: Heteroscedasticity robust VR test, pre-automation

K	AGA	ALW	BOPP	FML	GCB	GGBL	HFC	SCB	SGSSB	SWL	TBL	ASI
10	N/A	1.523**	2.398*	1.421	1.659*	1.482***	0.635	1.404	1.220**	1.013***	1.013***	1.023
15	N/A	1.751**	2.882*	1.441	1.773*	1.656**	0.590	1.538	1.222**	1.020**	1.020**	1.026

20	N/A	2.034***	3.241*	1.512***	1.954*	1.768**	0.480	1.571	1.142***	1.028**	1.028**	1.058
25	N/A	2.246**	3.439*	1.602***	2.135*	1.855**	0.407	1.588	1.018	1.035**	1.035**	1.178

Table 9A: Homoscedasticity robust VR test, post-automation

K	AGA	ALW	BOPP	FML	GCB	GGBL	HFC	SCB	SGSSB	SWL	TBL	ASI
10	0.102	0.099*	0.110*	0.096	0.127*	0.104	0.094*	0.083*	0.115**	0.102	0.102	0.109*
15	0.069	0.068*	0.079*	0.065	0.072*	0.071	0.057*	0.058**	0.075**	0.069	0.069	0.077*
20	0.052	0.050*	0.054*	0.050	0.058*	0.053	0.045*	0.043**	0.044**	0.052	0.052	0.061*
25	0.042	0.040**	0.045*	0.040	0.050*	0.042	0.037**	0.034**	0.034**	0.042	0.042	0.044*

Table 9B: Heterocedasticity robust VR test, post-automation

K	AGA	ALW	BOPP	FML	GCB	GGBL	HFC	SCB	SGSSB	SWL	TBL	ASI
10	1.013***	1.253**	1.264	0.941	1.412	1.482***	0.635	1.404	1.220**	1.013***	1.013**	1.771*
15	1.020**	1.398**	1.182	0.891	1.512	1.656**	0.590	1.538	1.222**	1.020**	1.020**	2.138*
20	1.028**	1.458**	1.148	0.871	1.717	1.768**	0.480	1.571	1.142***	1.028**	1.028**	2.473*
25	1.035**	1.496**	1.123	0.863	1.866**	1.856**	0.407	1.588	1.018	1.035**	1.035**	2.713*

6 Conclusions and policy implications

Automation is expected to improve stock market efficiency by improving the efficiency of information dissemination? This study therefore examined the impact automating the GSE has had on its efficiency, using daily stock returns data from 2006 to 2011. To test the automation-efficiency linkage, the trading days from 14 November 2008 to 27 March 2009 were excluded, since during this period the GSE operated both manual and electronic listings. The before–after approach was used. Various econometric techniques, including unit root, the Lo and Mackinlay Variance Ratio, and GARCH (1,1), were used. The analysis involved both the aggregate and the firm-level impact of the automation of the exchange. The preliminary findings reveal asymmetry in the distribution of GSE market returns.

The aggregate results from the unit root test of the random walk hypothesis, for all three cases, showed stationary market return series – an indication of the weak-form market inefficiency of the GSE. Further tests of the null hypothesis of random walk based on the GARCH (1,1) model showed similar results. Post-automation, the GSE remained inefficient, which implies that the automation of the exchange has not improved stock market efficiency in Ghana. However, further analysis of the GARCH model revealed that three things happened post-automation: First, news is impounded into prices more rapidly; second, old news has less persistence effect on price changes; and third, the quantity of information flowing into the market has increased. These results imply that the number of market participants involved in the market has increased, albeit that the GSE has remained inefficient post-automation.

An analysis of the stock market efficiency of the microstructure of the GSE post-automation produced mixed results. There is evidence of changing efficiency patterns at the firm level. Whereas some firms which had been efficient prior to automation became inefficient post-automation, others became efficient during that period, despite having been inefficient pre-automation. This suggest that the migration of the exchange into a fully automated platform benefited some equities more than others. However, it must emphasised that the efficiency of certain equities remained robust throughout the transition period.

Given the findings of this study, we recommend the following: First, the trading rules of the exchange must be ammended to allow online trading services to enable investors with the expertise to make their own trading decisions, independent of the services of a certified stockbroker. This has the advantage of faster transactions, low commission charges, and will tend to increase market volumes and capitalisation while enhancing competition in the market (because it opens the exchange to investors and brokers in other countries interested in investing in frontier markets). This will further allow the exchange to respond faster to changing trends in market fundamentals in real time. Also, since efficiency thrives immensely on information flow, data on the exchange should be made easily accessible to the public – potential investors especially – so as to improve the efficiency of the market. Further, lessons from the recent financial crises indicate that in as much as full automation is beneficial, the regulation of activities on the exchange is paramount in guaranteeing the efficient functioning of the capital market, if it is to play a key role in the development of the financial sector, as any regulation failure can lead to an asset bubble burst, with dire consequences for the entire economy.

Biographical notes

Justice Tei Mensah is a PhD candidate in Economics at the Swedish University of Agricultural Sciences (SLU). He holds a Master of Philosophy (MPhil) in Economics from the University of Ghana, and a Bachelor of Arts (BA) in Economics from Kwame Nkrumah University of Science and Technology, Ghana. His main research interests include energy demand and efficiency, environmental management and policy, dynamic modeling, climate change and welfare analysis, economic growth and development, finance and macroeconomic management, and applied econometrics. He can be contacted at myjumens@gmail.com; justice.tei.mensah@slu.se

Philip K. Adom is an economist by training. He obtained his Bachelor's degree in Economics from the University of Cape Coast and an MPhil degree in Economics from the University of Ghana. He is currently an assistant lecturer at the Department of Banking and Finance, Professional Studies, University of Accra-Ghana. He has been researching into areas such as energy demand modelling and forecasting; energy efficiency management; financial economics; macroeconomics; applied time-series analysis; carbon emission, technical efficiency and structural change; food crisis and household welfare; food crisis; and child health and education. He can be contacted at adomonline@yahoo.co.uk

Maame Pomaa-Berko is an applied economist by profession. She holds a Master's in Economic Policy and Management from the University of Ghana. Having worked in the financial sector in Ghana for many years, her main areas of research include financial management, the stock market, and enterprenuership. She can be contacted at mamapoms@yahoo.com

Acknowledgements

The authors thank Paul Alagidede for his constructive and useful comments on an earlier draft of the article. Similar thanks go to Franklin Obeng-Odoom (editor) and an anonymous reviewer for their review and suggestions.

References

Acharya, V. and Pedersen, L. (2005). 'Asset pricing with liquidity risk', *Journal of Financial Economics*, vol. 77, pp. 375–410.

Adelegan, J.O. (2004). 'How efficient is the Nigerian stock market? Further evidence', *African Review of Money, Finance and Banking*, vol. 6, pp. 10–30.

Appiah-Kusi, J. and Menyah, K. (2003). 'Return predictability in African stock markets', *Review of Financial Economics*, vol. 12, no. 3, pp. 247–270.

Alagidede, P. (2011). 'Return behaviour in Africa's emerging equity markets', *The Quarterly Review of Economics and Finance*, vol. 51, pp. 133–140.

Alagidede, P. and Panagiotidis, T. (2009). ‘Modelling stock returns in Africa’s emerging equity markets’, *International Review of Financial Analysis*, vol. 18, pp. 1–11.

Asal, M. (2000). ‘Are there trends towards efficiency for the Egyptian stock market?’ Working Paper, School of Economics and Commercial Law, University of Goteborg, Sweden. Available at http://www.e-m-h.org/Asal.pdf (accessed 1 November 2013).

Ayadi, F.O. (1984). ‘The random walk hypothesis and the behaviour of share prices in Nigeria’, *Nigerian Journal of Economic and Social Studies*, vol. 26, no. 1, pp. 57–71.

Barnes, P. (1986). ‘Thin trading and stock market efficiency: The case of the Kuala Lumpur Stock Exchange’, *Journal of Business Finance & Accounting*, vol. 13, no. 4, pp. 609–617.

Barua, S.K. (1987). Some observations on the Report of the High Powered Committee on the Stock Exchange Reforms, Annual Issue of ICFAI, December.

Basu, P. and Gupta, R. (2005). ’Is India vulnerable to financial crisis? Lessons from the Asian experience’, paper presented at the 18th Australian Finance and Banking Conference, Sydney, 14–16 December 2005.

Benouda, O.S. and Mezzez, D.H. (2003). ‘The effects of automation on liquidity, volatility, stock returns and efficiency: evidence from the Tunisian stock market’, *Review of Middle East Economics and Finance*, vol. 1, no. 2, pp. 141–154.

Bollerslev, T. (1986). ‘Generalised autoregressive conditional heteroscedasticity’, *Journal of Econometrics*, vol. 31, pp. 307–327.

Borges, M.R. (2008). ‘Efficient market hypothesis in European stock market’, Working paper series, WP 20/2008/DE/CIEF, School of Economics and Management, Technical University of Lisbon.

Bowers, E. (2008). ‘Ghana Stock Exchange plans to introduce fully automated trading’, Available at http://www.bloomberg.com/apps/news?pid=newsarchive&sid=aEB.B7bi_iZE (accessed 2 November 2013).

Bradley, J.V. (1968). *Distribution-free statistical tests*. Englewood Cliffs, NJ: Prentice-Hall.

Brooks, C. and Burke, S.P. (2003). ‘Information criteria for GARCH Model selection: An application to high frequency data’, *European Journal of Finance*, vol. 9, no. 6, pp. 557–580.

Chan, K.C., Cup, B.E., and Pan, M.S. (1997). ‘International stock market efficiency and integration: A study of eighteen nations’, *Journal of Business Finance & Accounting*, vol. 24, no. 6, pp. 803–814.

Claessens, S., Dasgupta, S. and Glen, J. (1995). ‘Return behaviour in emerging stock markets’, *World Bank Economic Review*, vol. 9, pp. 131–152.

Cromwell, J.B., Labys, W.C., and Terraza, M. (1994). *Univariate tests for time series models*, Sage Publications, Thousand Oaks, CA.

Debysingh, N. and Watson, P.K. (2007). ‘Automation and efficiency in two emerging equity markets’, SALISES Working Paper 15. Available at https://sta.uwi.edu/salises/pubs/workingpapers/15.pdf (accessed 20 November 2013).

Dewotor, F.S. and Gborglah J. (2004). ‘The information content of stock prices in Ghana’, Databank Research Paper. Available at http://www.researchgate.net/publication/228289149_The_Information_Content_of_Stock_Prices_in_Ghana (accessed 20 November 2013).

Dickinson, J.P. and Muragu, K. (1994). ‘Market efficiency in developing countries: A case study of the Nairobi Stock Exchange’, *Journal of Business Finance and Accounting*, vol. 21, no. 1, pp. 133–150.

Efobi, U. (2010). 'The efficient market hypothesis: Realities from the Nigerian stock market', Available at http://covenantuniversity.academia.edu/EfobiUchenna/Papers (accessed 20 November 2013).

Engle, R.F. (1982). 'Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation', *Econometrica*, vol. 50, pp. 987–1007.

Enisan, A.A. and Olufisayo A.O. (2009). 'Stock market development and economic growth: Evidende from seven sub-Saharan African, countries', *Journal of Economics and Business*, vol. 61, pp. 162–171.

Fama, E. (1970). 'Efficient capital markets: A review of theory and empirical work', *Journal of Finance*, vol. 25, no. 2, pp. 383–417.

Freund, W.C. and Pagano, M.S. (2000). 'Market efficiency in specialist markets before and after automation', *Financial Review*, vol. 35, pp. 79–104.

Frimpong, J.M. (2008). 'Capital market efficiency: An analysis of weak-form efficiency on the Ghana Stock Exchange', *Journal of Money, Investment and Banking*, vol. 5, pp. 5–12.

Gilmore, C.G. and McManus, G.M. (2003). 'Random-walk and efficiency tests of Central European equity markets', *Managerial Finance*, vol. 29, no. 4, pp. 42–61.

Gandhi, D., Saadi, S., Ngouhouo, I., and Dutta S. (2005). 'Testing for nonlinearity and modeling volatility in emerging capital markets: The case of Tunisia', *International Journal of Theoretical and Applied Finance*, vol. 9, no. 7, pp. 1021–1050.

Gandhi, D.K., Saunders, A.S., and Woodward, R.S. (1980). 'Thin capital markets: A case study of the Kuwait stock market', *Applied Economics*, vol. 12, pp. 341–349.

Ghana Stock Exchange (2009). 'Review of stock market performance, 2009', Available at http://www.gse.com.gh/index1.php?linkid=21&archiveid=233&page=1&adate=24%2F02%2F2010 (accessed 20 November 2013).

Ghana Stock Exchange (2012). 'Market summary 2012'.

Granger C.W.J. and Anderson A.P. (1978). *An introduction to bilinear time series models*, Vaden hoeck and Reprecht, Gottingen.

Gupta, R. (2006). 'Emerging markets diversification: Are correlations changing over time?' International Academy of Business and Public Administration Disciplines (IABPAD) Conference, 3–6 January 2006, Orlando.

Hendershott, T. and Moulton, P.C. (2011). 'Automation, speed, and stock market quality: The NYSE's hybrid', *Journal of Financial Markets Journal of Financial Markets*, vol. 14, pp. 568–604.

Hsieh, D.A. (1989). 'Testing for nonlinear dependence in daily foreign exchange rates', *Journal of Business*, vol. 62, no. 3, pp. 339–368.

Hudson, R., Dempsey, M., and Keasy, K. (1996). 'A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices, 1935–1994', *Journal of Banking and Finance*, vol. 20, pp. 1121–1132.

Jain, P.K. (2005). 'Financial market design and the equity premium: Electronic versus floor trading', *The Journal of Finance*, vol. 6, pp. 2955–2985.

Jefferis, K. and Smith, G. (2005). 'The changing efficiency of African stock markets', *South African Journal of Economics*, vol. 73, no. 1, pp. 54–67.

Kendall, M.G. (1953). 'The analysis of economic time series', *Journal of the Royal Statistical Society*, vol. 96, pp. 11–25.

Lo, A.W. and Mackinlay, A.C. (1988). 'Stock market prices do not follow random walks: Evidence from a simple specification test', *The Review of Financial Studies*, vol. 1, no. 1, pp. 41–57.

Magnusson, M.A. and Wydick, B. (2002). 'How efficient are Africa's emerging stock markets?', *The Journal of Development Studies*, vol. 38, no. 4, pp. 141–156.

Malkiel, B.G. (2003). 'The efficient market hypothesis and its critics', *The Journal of Economic Perspectives*, vol. 17, no. 1, pp. 59–82.

Malkiel, B.G. (2007). *A random walk down Wall Street: The time-tested strategy for successful investing*, Norton and Company, Inc., New York.

Mecagni, M. and Sourial, M.S. (1999). 'The Egyptian stock market: Efficiency tests and volatility effects', International Monetary Fund Working Paper WP/99/4.

Mishra, K., Das, K., and Pradhan, B. (2009). 'Empirical evidence on Indian stock market efficiency in context of the global financial crisis', *Global Journal of Finance and Management*, vol. 1, pp. 149–157.

Mollah, A.S. (2007). 'Testing weak-form market efficiency in emerging markets: Evidence from Botswana Stock Exchange', *International Journal of Theoretical and Applied Finance*, vol. 10, no. 6, pp. 1077–1094.

Mollah, S. and Vitali, F. (2011). 'Stock market efficiency in Africa: Evidence from random walk hypothesis', paper submitted to the South Western Finance Conference, 2011. Available at http://southwesternfinance.org/conf-2011/swfa2011_submission_82.pdf.org (accessed 1 July 2012).

Ntim, C., Opong, K.K., and Danbolt, J. (2007). 'An empirical re-examination of the weak form efficient markets hypothesis of the Ghana stock market using variance-ratios tests', *African Finance Journal*, vol. 9, no. 2, pp. 1–25.

Okpara G.C. (2010). 'Monetary policy and stock market returns: Evidence from Nigeria', *J Economics*, vol. 1, no. 1, pp. 13–21.

Olowe, R. (1999). 'Weak-form efficiency of the Nigerian stock market: Further evidence', *African Development Review*, vol. 11, pp. 54–68.

Osei, A.K. (2002). 'Asset pricing and information efficiency of the Ghana stock market', AERC Research Paper 115, African Economic Research Consortium, Nairobi, March 2002.

Osei, K.A. (1998). 'Analysis of factors affecting the development of an emerging market: The case of Ghana stock market', AERC Research Paper No. 76. African Economic Research Consortium, Nairobi.

Oskooe, P.A.S. (2012). 'Emerging stock market efficiency: Nonlinearity and episodic dependences evidence from Iran stock market', *J. Basic. Appl. Sci. Res*., vol 2, no. 11, pp. 11370–11380.

Parkinson, J.M. (1984). 'The Nairobi Stock Exchange in the context of development of Kenya', *Savings and Development*, vol. 8, no. 4, pp. 363–370.

Pastor, L. and Stambaugh, R.F. (2003). 'Liquidity risk and expected stock returns', *Journal of Political Economy*, vol. 111, pp. 642–685.

Poshakwale, S. (1996). 'Evidence on weak form efficiency and day of the week effect in the Indian stock market', *Finance India*, vol. 3, pp. 605–616.

Poterba, J.M. and Summers, L.H. (1989). 'Mean reversion in stock prices: Evidence and implications', NBER Working Paper no. 2343.

Ross, S. (1987). 'The interrelations of finance and economics: Theoretical perspectives', *American Economic Review*, vol. 2, pp. 29–34.

Ryoo, H-J. and Smith, G. (2002). 'Korean stock prices under price limits: Variance ratio tests of random walks', *Applied Financial Economics*, vol. 12, pp. 545–553.
Samuels, J.M. and Yacout, N. (1981). 'Stock exchange in developing countries', *Savings and Development*, vol. 5, no. 4, pp. 213–230.
Sharma, J.L. and Kennedy, R.E. (1977). 'A comparative analysis of stock price behavior on the Bombay, London and New York Stock Exchanges', *The Journal of Financial and Quantitative Analysis*, vol. 12, no. 3, pp. 391–413.
Simons, D. and Laryea, S. (2006): 'Testing the efficiency of selected African markets', *Finance India*, vol. 20, no. 2, pp. 553–571.
Smith, G. (2008). 'Liquidity and the informational efficiency of African stock markets', *South African Journal of Economics*, vol. 76, no. 2, pp. 161–175.
Smith, G., Jefferis, K., and Ryoo, H-J. (2002). 'African stock markets: Multiple variance ratio tests of random walks', *Applied Financial Economics*, vol. 12, pp. 475–484.
World Bank (2006). 'Global development finance: The development potential of surging capital flows', Available at http://econ.worldbank.org (accessed 1 July 2012).

Appendix 1: Sectoral distribution of sampled companies of the GSE

A. Food & Beverage

1. Benso Oil Palm Plantation (BOPP)
2. Fan Milk Ghana Ltd (Fml)
3. Guinness Ghana Breweries Ltd (Ggbl)

B. Financial Institutions

4. Ghana Commercial Bank Ltd (Gcb)
5. HFC Bank Ltd (Hfc)
6. SG-SSB Ltd (Sg-ssb)
7. Standard Chartered Bank (Scb)
8. Trust Bank Ltd (TBL)

C. Manufacturing

9. Aluworks Ghana Ltd (Alw)
10. AngloGold Ashanti (AGA)
11. Sam Woode Limited (SWL)

1.0: Serial correlation test for post-automation GARCH model

Test name: Correlogram of squared standardised residuals

Sample: 2 684

Included observations: 683

Autocorrelation	Partial correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.002	-0.002	0.0027	0.959
.|. |	.|. |	2	-0.000	-0.000	0.0028	0.999
.|. |	.|. |	3	-0.013	-0.013	0.1122	0.990
.|. |	.|. |	4	-0.008	-0.008	0.1560	0.997
.|. |	.|. |	5	-0.013	-0.013	0.2748	0.998
.|. |	.|. |	6	0.004	0.004	0.2884	1.000
.|. |	.|. |	7	-0.005	-0.005	0.3035	1.000
.|. |	.|. |	8	0.065	0.064	3.2120	0.920
.|. |	.|. |	9	-0.008	-0.007	3.2521	0.953
.|. |	.|. |	10	0.009	0.009	3.3041	0.973
.|. |	.|. |	11	0.004	0.006	3.3182	0.986
.|. |	.|. |	12	-0.004	-0.003	3.3289	0.993
.|. |	.|. |	13	0.000	0.002	3.3289	0.996
.|. |	.|. |	14	-0.014	-0.015	3.4727	0.998
.|. |	.|. |	15	-0.009	-0.008	3.5278	0.999
.|. |	.|. |	16	-0.010	-0.014	3.5936	0.999
.|. |	.|. |	17	-0.007	-0.007	3.6317	1.000
.|. |	.|. |	18	-0.012	-0.013	3.7282	1.000
.|* |	.|* |	19	0.132	0.131	15.976	0.659
.|. |	.|. |	20	-0.019	-0.019	16.218	0.703
.|. |	.|. |	21	0.013	0.013	16.336	0.751
.|. |	.|. |	22	-0.003	0.001	16.344	0.798
.|. |	.|. |	23	-0.015	-0.013	16.493	0.833
.|. |	.|. |	24	0.010	0.015	16.564	0.867
.|* |	.|* |	25	0.092	0.094	22.641	0.599
.|. |	.|. |	26	-0.009	-0.007	22.699	0.650
.|. |	.|. |	27	0.012	-0.005	22.795	0.696
.|. |	.|. |	28	-0.025	-0.019	23.241	0.721
.|. |	.|. |	29	-0.013	-0.017	23.358	0.760
.|. |	.|. |	30	0.001	0.003	23.359	0.800
.|. |	.|. |	31	0.001	0.002	23.360	0.836
.|. |	.|. |	32	0.005	0.003	23.380	0.866
.|. |	.|. |	33	-0.017	-0.027	23.584	0.886
.|. |	.|. |	34	0.015	0.019	23.745	0.905
.|. |	.|. |	35	-0.015	-0.015	23.904	0.922
.|. |	.|. |	36	-0.016	-0.011	24.091	0.935

2.0: Serial correlation test for pre-automation GARCH model

Test name: Correlogram of squared standardised residuals

Sample: 2 685

Included observations: 684

Autocorrelation	Partial correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.007	-0.007	0.0332	0.855
.|. |	.|. |	2	0.002	0.002	0.0357	0.982
.|. |	.|. |	3	-0.009	-0.009	0.0939	0.993
.|* |	.|* |	4	0.090	0.090	5.7384	0.220
.|. |	.|. |	5	-0.003	-0.002	5.7455	0.332
.|. |	.|. |	6	0.009	0.009	5.8058	0.445
.|. |	.|. |	7	-0.009	-0.007	5.8565	0.557
.|. |	.|. |	8	-0.004	-0.012	5.8662	0.662
.|. |	.|. |	9	-0.006	-0.005	5.8878	0.751
.|. |	.|. |	10	-0.008	-0.010	5.9353	0.821
.|. |	.|. |	11	-0.001	0.001	5.9356	0.878
.|. |	.|. |	12	-0.009	-0.008	5.9890	0.917
.|. |	.|. |	13	-0.008	-0.007	6.0341	0.945
.|. |	.|. |	14	-0.007	-0.005	6.0637	0.965
.|. |	.|. |	15	-0.009	-0.009	6.1209	0.978
.|. |	.|. |	16	-0.007	-0.006	6.1578	0.986
.|. |	.|. |	17	-0.005	-0.004	6.1783	0.992
.|. |	.|. |	18	-0.003	-0.002	6.1847	0.995
.|. |	.|. |	19	-0.008	-0.007	6.2325	0.997
.|. |	.|. |	20	-0.008	-0.007	6.2786	0.998
.|. |	.|. |	21	-0.009	-0.009	6.3409	0.999
.|. |	.|. |	22	-0.009	-0.010	6.4043	1.000
.|. |	.|. |	23	-0.009	-0.008	6.4630	1.000
.|. |	.|. |	24	-0.008	-0.007	6.5043	1.000
.|. |	.|. |	25	-0.003	-0.002	6.5129	1.000
.|. |	.|. |	26	-0.001	0.000	6.5133	1.000
.|. |	.|. |	27	0.001	0.002	6.5135	1.000
.|. |	.|. |	28	-0.007	-0.006	6.5452	1.000
.|. |	.|. |	29	-0.008	-0.009	6.5962	1.000
.|. |	.|. |	30	0.009	0.008	6.6544	1.000
.|. |	.|. |	31	-0.008	-0.009	6.6979	1.000
.|. |	.|. |	32	-0.007	-0.007	6.7314	1.000
.|. |	.|. |	33	-0.005	-0.005	6.7516	1.000
.|. |	.|. |	34	-0.007	-0.009	6.7828	1.000
.|. |	.|. |	35	-0.009	-0.008	6.8423	1.000
.|. |	.|. |	36	0.002	0.002	6.8444	1.000

3.0: Serial correlation test for full-period GARCH model

Test name: Correlogram of squared standardised residuals

Sample: 2/20/2006 12/30/2011

Included observations: 1457

Autocorrelation	Partial correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.005	-0.005	0.0426	0.837
| |	| |	2	0.001	0.001	0.0432	0.979
| |	| |	3	-0.007	-0.007	0.1150	0.990
| |	| |	4	0.040	0.040	2.4449	0.655
| |	| |	5	-0.004	-0.003	2.4632	0.782
| |	| |	6	0.003	0.003	2.4744	0.871
| |	| |	7	-0.006	-0.006	2.5336	0.925
| |	| |	8	0.004	0.002	2.5556	0.959
| |	| |	9	-0.005	-0.005	2.5914	0.978
| |	| |	10	-0.003	-0.003	2.6026	0.989
| |	| |	11	-0.002	-0.002	2.6101	0.995
| |	| |	12	-0.007	-0.007	2.6749	0.997
| |	| |	13	-0.000	-0.000	2.6752	0.999
| |	| |	14	-0.006	-0.006	2.7318	0.999
| |	| |	15	-0.007	-0.007	2.7955	1.000
| |	| |	16	-0.006	-0.006	2.8548	1.000
| |	| |	17	-0.004	-0.004	2.8820	1.000
| |	| |	18	-0.004	-0.003	2.9006	1.000
| |	| |	19	0.003	0.003	2.9152	1.000
| |	| |	20	-0.007	-0.007	2.9981	1.000
| |	| |	21	-0.004	-0.004	3.0188	1.000
| |	| |	22	-0.007	-0.007	3.0940	1.000
| |	| |	23	-0.007	-0.008	3.1757	1.000
| |	| |	24	-0.005	-0.005	3.2144	1.000
| |	| |	25	0.006	0.006	3.2611	1.000
| |	| |	26	-0.002	-0.002	3.2673	1.000
| |	| |	27	0.007	0.007	3.3357	1.000
| |	| |	28	-0.007	-0.006	3.4006	1.000
| |	| |	29	-0.004	-0.005	3.4273	1.000
| |	| |	30	0.003	0.003	3.4419	1.000
| |	| |	31	-0.008	-0.008	3.5270	1.000
| |	| |	32	-0.006	-0.006	3.5806	1.000
| |	| |	33	-0.006	-0.006	3.6384	1.000
| |	| |	34	0.044	0.044	6.5204	1.000
| |	| |	35	-0.008	-0.008	6.6267	1.000
| |	| |	36	0.014	0.014	6.9225	1.000