TESTING WEAK-FORM MARKET EFFICIENCY IN EMERGING MARKET: EVIDENCE FROM BOTSWANA STOCK EXCHANGE

A. SABUR MOLLAH

Department of Accounting & Finance
Faculty of Business, University of Botswana
Private Bag UB 00701, Gaborone, Botswana
mollahas@mopipi.ub.bw
sabur0112@yahoo.co.uk

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Market efficiency is an area of enormous interest in financial literature. Numerous researchers conducted empirical studies in testing weak-form market efficiency in several stock markets and employed various techniques but the empirical evidence is controversial. Triangulation econometric approach is employed to assess the predictability of daily return series of Botswana Stock Exchange (BSE) and to test the null hypothesis of random walk model. The empirical results reject the null hypothesis of random walk model for the daily return series of BSE for the period of 1989–2005 and evidenced serial autocorrelation of return series, which clearly indicate predictability and volatility of security prices of Botswana market. However, the empirical evidence of both non-parametric (Kolmogrov–Smirnov: normality test and run test) and parametric test (Auto-correlation test, Auto-regressive model, ARIMA model) reject the hypothesis of random walk model and indeed violate the notion of weak-form market efficiency.

Keywords: Weak-form market efficiency; emerging market.

1. Introduction

There is a substantial body of literature on market efficiency and stock return behavior but most of them concentrated in the developed stock markets particularly US market. However, the needs of more research in the emerging and less developed markets are well recognized. As noted by Claessens et al. [12], "...little is known about the time series properties of returns and the price determination process in these markets (cited in [47, p. 300])." Wai and Patrick [48] emphasized the need for studies on the performance and structure of capital markets in developing countries. According to them, the most profitable line of research would be in detailed case studies of capital markets in specific (developing) countries. Furthermore, Drake [16] noted, "More research is needed about market structure, performance and potential in individual countries (p. 89)." Drake also showed an optimistic attitude towards

the prospects for, and the possible benefits of securities market development especially in less developed countries. The necessity of more research in the emerging and less developed market is also noted by Akdeniz *et al.* [2], "...it is evident that much has to be done to understand the nature of stock returns in emerging markets [p. 25]".

Most of the researches conducted on stock returns in emerging and less developed markets are characterized by high volatility and predictability [25]. Further, Bekaert et al. [4] present evidence that the distribution of emerging equity market return is potentially unstable and differ in the 1990s than in the 1980s. Later Bekaert et al. [3] stated that research in emerging markets suggested high volatility and low correlation both across the emerging markets and with the developed markets. However, Shleifer [43] stated that the key forces by which markets are supposed to attain efficiency, such as arbitrage and investors' rationality is contradicted with the psychological and institutional evidence in the real world. For instance, arbitrage is limited as it relies crucially on the availability of close substitutes. However, he introduces "behavioral finance" as an alternative view of financial markets. According to this new view, economic theory does not lead us to expect financial markets to be efficient. Rather, systematic and significant deviations from efficiency are expected to persist for longer periods of time.

The Botswana Stock Exchange (BSE), is one of the representatives of an emerging market during the period with rapid growth in terms of market capitalization, trade volume and the number of listed companies. The lack of research in Botswana Stock Market, where the stock exchange has largely developed after 1990s, the structure, functioning, efficiency and the determinants of share returns are the research questions, which need addressing. BSE is the third largest stock exchange amongst the Sothern African Stock Exchanges (SADC exchanges). In Botswana, the pace of industrialization has suffered in the past due to factors like, import oriented country, lack of entrepreneurs, and low level of productivity. However, with the spree of privatization and the success of stock markets in many of the Southern African Newly Industrialized Countries (NICs), Botswana presents an optimistic ground for effectively developing and utilizing the capital market for industrial financing.

With respect to the securities market in Botswana, foreign and national experts have undertaken very few studies (for example, [9, 45, 46]). All of these studies mainly focused on the development aspects of BSE and suggest remedies for the improvement of the market. This study mainly seeks evidence of market efficiency and keen to see whether Botswana Stock Market return series is independent or follows random walk model.

The remainder of the paper is divided into four sections. Analytical framework and literature review is in Sec. 2. Section 3 describes the data and method. The empirical results are reported in Sec. 4. Finally, concluding remarks are incorporated in Sec. 5.

2. Analytical Framework and Literature Review

The analytical framework of examining the stock price behavior will not only focus on the movements of stock price but also on the weak form efficiency of the market. The study employs random walk model (both with drift and without drift) in different tests. When the successive price changes are independent and identically distributed (i.e., it shows no uniform pattern) means the price changes follow random walk. Random walk model (RWM) implies that price changes are serially independent and thereby produces error term which is a white-noise process. RWM does not assume that the mean of the distribution is independent but says that the entire distribution is independent condition at the information available. If one-period returns are independent, identically distributed, prices will not follow a random walk since the distribution of price changes will depend on the price level. So, the RWM states that the sequence (the order) of the past returns is of no consequence in assessing distributions of future returns. The random walk is the extension of fair game model. While the fair game model states the condition of market equilibrium can be stated in terms of expected returns but the random walk model states detail about the stochastic process of generating returns. Under the random walk model, the behavior of prices under the EMH will wander randomly with or without drift (around an increasing trend). A random walk model with drift implies that the expected price changes can be non-zero. A stochastic variable is said to follow random walk with drift parameter δ , when

$$X_{t+1} = \delta + X_t + \varepsilon_{t+1}, \tag{2.1}$$

where ε_{t+1} is an identically and independently distributed random variable: $\Sigma \varepsilon_{t+1} = 0$, and a random walk without drift $\delta = 0$.

However, the sub martingale model held that the expected value of next period's price projected on the basis of information is equal to or greater than current prices. A sub martingale assumption hold implies trading rules based only on information sequence cannot have greater profits than a policy of always buying and holding the security during the future period in question.

When the expected return and price changes are zero means that the price sequences follow a martingale. As for example, if we have a stochastic variable X_t , which has the property:

$$\sum \frac{X_{t+1}}{\Phi_t} = X_t. \tag{2.2}$$

Then X_t is said to be a martingale where the best forecast of all future values of X_{t+i} ($i \ge 1$) is the current value of X_t . When the agent knows X_t , no other information in Φ_t helps to improve the forecast. Clearly, X_{t+1} is a martingale and change in $X_{t+1} = X_{t+1} - X_t$ is a fair game (for $\delta = 0$). In the efficient market literature, when it is said that stock price follows martingale include dividend because the dividend price ratio is non-zero and are not constant, so the (log of the) price level cannot

be martingale. In fact, any increase in the expected capital gain must be exactly offset by a lower expected dividend yield.

Moreover, the random walk is more restrictive than a martingale since a martingale does not restrict the higher conditional moments to be statistically independent. For example, if the prices of stock (including any dividend payments) are a martingale then successive price changes are unpredictable but it allows the conditional variance of the price changes to be predictable from past variances. But time varying conditional variances is not available if prices follow a random walk.

Though it is generally believed that the emerging markets are less efficient, the empirical evidence does not always support the thought. The evidence on weak form efficiency is controversial especially in developing and less developed countries market. In an early comparative study, Sharma and Kennedy [42] found weak form efficiency on the Bombay Stock Exchange similar to the London Stock Exchange and the New York Stock Exchange. On the other hand, Roux and Gilbertson [41] and Abrosimova et al. [1] found weak form inefficiency on the Johannesburg and Russian Stock Exchanges. Similarly, Ghandi et al. [21] found evidence that the Kuwaiti Stock Market was not weak form efficient. However, Errunza and Losq [17] stated that less developed countries markets were quite comparable to European small markets and were not efficient as developed countries markets, while Branes [5] tested the weak form market efficiency on the Kuala Lumpur Stock Exchange and concluded that the returns exhibited a surprisingly high degree of efficiency despite the problem of thin trading. But at the same time, Laurence [31] found a little deviation of the WFEMH in Kuala Lumpur and Singapore Stock Exchange. Similarly, Chan et al. [8] had attempted to examine the integration among the emerging markets in view of globalization of the stock markets and evidenced that the stock prices in major Asian markets and US markets were weak form efficient individually and collectively in the long run. The findings imply that international diversification among the market is effective. On the contrary, Butler and Malaikah [7] examined efficiency and inefficiency in two thinly traded stock markets in the Middle East. The authors noted that individual stocks of Kuwaiti market was similar to other thinly traded market exhibiting statistically significant auto-correlation whereas all stocks (sample) of the Saudi market showed a significant departure from random walk. Similarly, Cheung et al. [10] reported inefficiency in the stock markets of Korea and Taiwan, whereas Dickinson and Muragu [15] provided evidence consistent with the market efficiency on the Nairobi Stock Exchange. They concluded that small market such as Nairobi Stock Exchange (provided a low serial correlation of stock returns) was weak form efficient. Contrary to this, Urrutia [47] rejected the weak form efficiency in four Latin American emerging markets although his findings were not consistent between the two tests he used. In short, most of the studies conducted in the less developed markets evidence the existence of weak form inefficiency. As for example, in a World Bank study, Claessens et al. [13] reported significant serial correlation in equity returns from 19 emerging markets and suggested that stock prices in emerging markets violate weak form EMH. Similar findings were reported

by Harvey [24] for most emerging markets. Similarly, Poshakwale [38, 39] found that the Indian market was not weak form efficient. Moreover, Khababa [29] had examined the behavior of stock price in the Saudi Financial market seeking evidence for weak form efficiency and suggested that the market was not weak form efficient. On the other hand, Ojah and Karemera [35] found weak form efficiency in four Latin American's emerging market except Chile. So, the findings from emerging markets are controversial. However, the findings of less developed markets are also interpreted in different ways. As suggested by Goldman and Sosin [22], market inefficiency results from barriers to dissemination of information, which depends positively on the real cost of capital to speculators and negatively on the speed of information dissemination (cited by [17, p. 574]). Moreover Errunza and Losq [17] stated that a lower degree of efficiency in less developed countries markets might be due to common characteristics of loose disclosure requirements, thinness and discontinuity in trading and less developed nature of the markets. They concluded that the independence hypothesis might be justified by the existence of risk free assets, negligible non-diversifiable risk and perfect market assumption. Clearly, conditions in less developed countries are further away from this idealised vision of the world than in major developing countries markets. Butler and Malaikah [7] concluded that institutional factors contributing to market inefficiency include illiquidity, market fragmentation, trading and reporting delays and the absence of official market makers. Similarly, Khababa [29] and Onour [36] explained that the inefficiency in the Saudi Financial market might be due to delay in operations and high transaction costs, thinness of trading and illuiquidity in the market. On the other hand, Dickinson and Muragu [15] and Moustafa [34] who did evidence supporting the weak form efficiency on the Nairobi and United Arab Emirates Stock Exchanges and explained that in spite of thinness of the market, the information were disseminated because of sophisticated communication through business journal and other media.

Overall, the results of previous research evidence that the markets of developed economies are generally weak form efficient. That means the successive returns are independent and follows random walk (see, for example, [18, 19]). On the other hand, the research findings on the market of developing and less developed countries are controversial. Based on the mixed results the emerging market equities require clarification. Comparison and needed additional information on equity price dynamics is a vital segment of the world's emerging capital markets. So, it is an interesting empirical question whether and to what extent the less developed market is efficient and what return generation factors drives the markets.

3. Data and Method

Daily market return of Botswana Stock Exchange (BSE) for the period of 1989–2005 is considered for the empirical analysis of this paper. This study uses domestic equity price indices daily time series data because this is the only available index data series in BSE at this moment. The non-availability of databases has had a significantly

limiting effect on market studies in developing countries, and consequently on the volume of published evidence [15]. One probable solution to this problem is to use the indices of the index, which are available (see, for example, [21, 42]).

The empirical test in the study uses multi-approach or triangulation of statistical techniques rather than individual approach, which makes it easier to compare the results from different findings and increases reliability of this research. This study includes both non-parametric tests (such as: Kolmogrov-Smirnov goodness of fit test and run test) and parametric tests (such as: Auto-correlation coefficient test, Auto-regression test and dynamic time series model Auto-regressive Integrated Moving average model (ARIMA)). In choosing the analytical techniques we have considered the following issues: firstly, the research needed triangulation between developed and less developed markets (supporting the view of [15]). Triangulation in research may be theoretical or implemented through the use of different research methods, different settings, different data and improved decision making techniques and so on. Secondly, the study considers both robust traditional tests (such as: run test and auto-correlation test) and dynamic time series techniques (such as: Autoregression test and ARIMA model), which perhaps claim better findings. Thirdly, a recent approach to the study of the predictability of stock market returns in developed markets also includes the variance ratio test [31] and regression analysis [27, 40]. This study also employs the time series regression analysis considering the lag of returns and current returns in Auto-regression analysis, which helps to determine whether the returns are predictable from the past returns and also to find the extent of dependency. Finally, the robustness of the results is assessed in various ways, e.g., the use of different testing procedure helps to reach a final conclusion and to examine the consistency of the findings (e.g., [47] finds different findings from run test and variance ratio test). In short, this study restricts attention exclusively for the predictability of returns in a less developed market using the combinations of robust and dynamic techniques. However, this study generally follows the methodology used by [13, 32, 39] in emerging markets. Moreover, there are some additional time series models used in this study such as: auto-regression analysis and ARIMA model to confirm the results of other analysis as well as to see the predictive ability of the fitted model. In the return predictability, this study excludes the "week-end effect", which have been documented internationally [26] and these effects largely persist despite different institutional arrangements [6].

The daily market returns are used as an individual time—series variable.² The daily share price indices include all the listed domestic stock. The study calculates market returns from the daily price indices without adjustment of dividend, bonus and right issues. The reason is that many researchers confirm that their

¹Claessens et al. [13] use two different additional tests such as variance ratio test and cross-sectional regression analysis and Poshakwale [39] includes the week-end effect.

² "The EMH gives no indication of the horizon over which the returns should be calculated. The tests therefore be done for alternative holding period of a day, week, month or even years." [14, p. 117].

conclusions remain unchanged whether they adjusted their data for dividend or not (for example, [20, 30]). As mentioned earlier, this study mainly uses the daily market returns as an individual variable in time series analysis.

Daily market returns (R_{mt}) are calculated from the daily price indices such as follows:

$$R_{mt} = Ln\left(\frac{PI_t}{PI_{t-1}}\right) \tag{3.1}$$

where, R_{mt} = market return in period t; PI_t = price index at day t; PI_{t-1} = the price index at period t-1 and Ln = natural log.

The reasons to take logarithm returns are justified both theoretically and empirically. Theoretically, logarithmic returns are analytically more tractable when linking together sub-period returns to form returns over longer intervals.³

Moreover, empirically logarithmic returns are more likely to be normally distributed which is a prior condition of standard statistical techniques [33, 44].

4. Empirical Evidence

The empirical results are discussed according to each individual statistical analysis. One of the basic assumptions of the random walk model is that the distribution of the return series should be normal. Under the random walk model, the behavior of prices under the EMH will wander randomly with or without drift (around an increasing trend). A random walk model with drift implies that the expected price changes can be non-zero [Eq. (2.1)]. In order to test the distribution of the return series, the descriptive statistics of the log of the market returns are calculated and presented on the Table 1.

From the Table 1, it can be seen that the frequency distribution of the return series is not normal. The skewness coefficient in excess of unity, generally taken to be fairly extreme [11, p. 109]. It is evidenced a negative skewness (-2.316) in Botswana market. In a Guassian distribution, one would expect these data to have a kurtosis coefficient of 2.902.⁴ Kurtosis generally either much higher or lower indicates extreme leptokurtic or extreme platykurtic [33, 37]. Our evidence of the value of (498.171) falls under the extreme leptokurtic distribution. Generally, values for skewness zero and kurtosis 3 represents that the observed distribution is perfectly

Table 1. Descriptive statistics of the daily market return (log of the market returns).

Variable	Mean	Std.	Minimum	Maximum	Skewness	Kurtosis
LnRmt	0.001609	0.0165538	-0.4651	0.4251	-2.316 (0.052)	498.171 (0.104)

³Poshakwale [39] described about this clearly.

⁴Kendall [28] calculated the expected normal kurtosis equal to 2.902[3(n-1/n+1)=2.902], where n= sample size.

normally distributed. So negative skewness and leptokurtic frequency distribution of stock return series on the Botswana indicates that the distribution is not normal. In other words, the non-normal frequency distributions of the stock return series deviate from the prior condition of random walk model. To confirm the distribution pattern of the stock return series, Kolmogrov–Smirnov Goodness of Fit test is also used, which provides further evidence whether the distribution confirms to a normal distribution or not. It is important to note that this study uses two different non-parametric tests; one is Kolmogrov–Smirnov Goodness of fit test and another is run test to prove if the daily return series follows random walk model.

Kolmogrov–Smirnov Goodness of fit test (K-S test) is a non-parametric test and is used to determine how well a random sample of data fits a particular distribution (uniform, normal and Poisson). The one sample K-S test compares the cumulative distribution function for a variable with a uniform or normal distribution and test whether the distributions are homogeneous. We used both normal and uniform parameters to test the distribution. Results from the Table 2, (K-S test) shows a 0.00 probability for the Z (13.319), clearly indicates that the frequency distribution of the daily return series of Botswana Exchange does not fit by normal distribution. However, the normality test of both descriptive statistics and the K-S test document that the return series exhibits non-normal distribution. The extreme leptokurtic distributions of the stock return series of Botswana resembles as found in other markets such as Australia and New Zealand [23], India [38, 39], Bangladesh [33] and Kuala Lumpur and Singapore [31] Stock Markets.

The run test is another non-parametric test approach to test and detect statistical dependencies (randomness), which may not be detected by the parametric auto-correlation test. The test is well known and widely used to prove the random-walk model because it ignores the properties of distribution. Null hypothesis of the test is that the observed series is a random series. The numbers of runs are computed as a sequence of the price changes of the same sign (such as: ++, --, 0 0). When the expected number of run is significantly different from the observed number of runs implies that the null hypothesis of randomness of the daily return series is rejected. The run test converts the total number of runs into a Z statistic. For large samples the Z statistics gives the probability of difference between the actual and expected number of runs. The Z value is greater than or equal to \pm 1.96; reject the null hypothesis at 5% level of significance [42].

The question of whether a sequence of observed numbers (i.e., the individual company's daily share price series or daily share price index series) is a random sequence can be studied by the number of runs observed in the series. The number of run is computed as a sequence of the price change of the same sign. The actual

Table 2. Kolmogrov-Smirnov goodness of fit test: Daily market return.

Absolute	Positive	Negative	K-S Z	Z- Tailed P
0.283	0.262	-0.283	13.319	0.000

number of run is compared with the expected number of runs, irrespective of sign. The null and alternate hypothesis for the run test is as follows:

H0: The observed series is a random series.

H1: The observed series is not a random series.

The test statistics for the number of runs is computed as follows:

Expected number of Runs
$$(R)$$
, $E(R) = n + 2/2$, $Var(R) = n(n-2)/4(n-1)$,

The actual number of runs (R) is computed as $\sum_{i=1}^{n} Ri$, where $R_i = 1$, if $\mu i < \mu i + 1$, i = 1, 2, ..., n, = 0, otherwise.

The test statistics $Z = \frac{R - E(R)}{\sqrt{\text{var}(R)}}$.

As can be seen from the Table 3 that the Z statistics of daily market return is greater than ± 1.96 and negative, which means that the observed number of runs is fewer than the expected number of runs with observed significance level. The result implies a lagged response to information.⁵ In addition to that, the observed numbers of run also indicates to reject or accept the random walk model.

The number of runs is greater than 20 (Table 3) states that the series return are not following the independent assumption of random walk model. Therefore, we can reject the null hypothesis that the return series of Botswana follows random walk. However, the significant two-tailed with negative Z values (-3.524) greater than ± 1.96 also suggest non-randomness because of too few observed numbers of runs than expected. The results are similar to the findings of [33, 39], who also document the actual number of runs significantly lower than expected number of runs for daily returns in India, Philippines, Malaysia and Thailand. Overall, the results of run test analysis on Botswana market indicates that the distribution of the daily share return series on the exchange are not random as the probabilities associated with expected number of runs are all greater than the observed number of runs.

The study investigates the parametric tests to examine if the findings of non-parametric tests confirmed by the findings of parametric tests. In addition, the extent of dependency is also measured with the parameters estimated.

Table 3. The results of run test (daily market return series and individual return series).

Particulars of the variables			Asymp sig (2-tailed)
Daily market return	1028	-3.524*	0.000

^{*}Denotes significant at 1% level.

⁵ As the Table value does not represent the expected number of runs, we also calculate the expected number of runs following the formula used by Urrutia [47]. Expected number of runs = 2(n+1)/3; where n = number of observations; and the results shows that there is a significant difference between the observed number of runs and expected number of runs.

Auto-correlation test is conducted in testing of either dependence or independence of random variables in a series. This test is popularly used in a number of studies (e.g., [13, 23, 29, 31, 33, 39]). The serial correlation coefficient measures the relationship between the values of a random variable at time t and its value in the previous period. Auto-correlation tests evidence whether the correlation coefficients are significantly different from zero.

The basic model for Auto-correlation analysis and for Ljung-Box statistics is:

$$U_t = \operatorname{Ln} R_{mt} - \operatorname{Ln} R_{mt-1}. \tag{4.1}$$

The auto-correlation co-efficient has been measured by

$$rn = [Covariance(U_t, U_t - 1) / [variance(U_t)],$$

where rn is the nth order of auto-correlation coefficient or auto-correlation coefficient having n-period lag, U_t is the change of log price of period t to t-1.

In this study, the sample autocorrelation coefficient for daily changes in price has been computed for lag n = 1, 2, 3, ..., 22.

This study used auto-correlation analysis for a large sample (numbers of observations)

Ljung–Box statistics that follows the chi-square distribution with m degrees of freedom:

$$LB = n(n+2) \sum_{k=1}^{m} (\hat{P}_k^2/n - k) \sim \chi^2,$$

where, $\hat{P_k} = \text{Auto-correlation coefficients at lag } k, n = \text{sample size.}$

In this study, the auto-correlation coefficients have been computed for the log of the market return series showing significant auto-correlation at different lags for the sample period. The results of auto-correlation are presented on the Table 4. It is evident that there is significant (positive sign) auto-correlation coefficient at all lags except 1st, 10th, 14th, 18th, 26th, and 28th lag. The presence of non-zero auto-correlation coefficients in the log of the market returns series clearly suggests that there is a serial dependence between the values. However, the results from the Table 4 confirm that there is a significant auto-correlation of daily market returns for the sample period,. The non-zero auto-correlation of the series associated with Ljung-Box Q statistics that are jointly significant at 1% level at 30 degrees of freedom (lags) suggest that the return series of Botswana does not follow the random walk model.

The results of auto-correlation tests found in this study are consistent with the findings of [13, 24, 33, 39] in emerging market research. They also find significant predictability of return in emerging markets while comparing the results of emerging markets with the developed markets [24, 25]. Similarly, Claessens et al. [13] find that most industrial economies, first-order auto-correlation are not generally higher than 0.2, whereas in eight economies in emerging market (such as Chile, Colombia, Mexico, Pakistan, Philippines, Portugal, Turkey and Venezuela) have significant first order auto-correlation greater than 0.20. The 1st order autocorrelation of this

study is -0.327, which is also higher than 0.20 but the highest first order auto-correlation was 0.489 in Colombia. Poshakwale [39] and Mobarek *et al.* [33] also evidence significant auto-correlation at various lags of the return series in India, Bangladesh, Philippines, Malaysia and Thailand suggests interdependence in the return series. So, the results found in the study are not inconsistent with the findings in other emerging markets.

This study uses exact maximum likelihood auto-regression technique to examine whether there is non-zero significant relationship exist between current return series with the first and second lag values of itself. The co-efficient significantly different from zero indicates the predictability of share return from the past return. In the context of weak form of efficient market hypothesis (WFEMH), the regression model used according to law:

$$LnP_t = a_1 + a_2 Ln P_{t-1} + U_t, (4.2)$$

Table 4. Results of Auto-correlation test (log of the daily market return).

			Box-Ljung Statistic		
Lag	Autocorrelation	Std. Error ^a	Value	df	Sig.b
1	-0.327	0.021	2380.146	1	0.000
2	0.034	0.021	2400.689	2	0.000
3	0.056	0.021	2470.712	3	0.000
4	0.062	0.021	2560.259	4	0.000
5	0.039	0.021	2590.664	5	0.000
6	0.048	0.021	2640.850	6	0.000
7	0.021	0.021	2650.806	7	0.000
8	0.042	0.021	2690.774	8	0.000
9	0.040	0.021	2730.301	9	0.000
10	-0.003	0.021	2730.317	10	0.000
11	0.064	0.021	2820.406	11	0.000
12	0.008	0.021	2820.550	12	0.000
13	0.009	0.021	2820.719	13	0.000
14	-0.001	0.021	2820.720	14	0.000
15	0.060	0.021	2900.895	15	0.000
16	0.010	0.021	2910.134	16	0.000
17	0.025	0.021	2920.479	17	0.000
18	-0.013	0.021	2920.855	18	0.000
19	0.050	0.021	2980.364	19	0.000
20	0.023	0.021	2990.533	20	0.000
21	0.024	0.021	3000.841	21	0.000
22	0.015	0.021	3010.363	22	0.000
23	0.009	0.021	3010.533	23	0.000
24	0.005	0.021	3010.599	24	0.000
25	0.023	0.021	3020.816	25	0.000
26	-0.008	0.021	3020.971	26	0.000
27	0.033	0.021	3050.374	27	0.000
28	-0.014	0.021	3050.840	28	0.000
29	0.011	0.021	3060.100	29	0.000
30	0.023	0.021	3070.336	30	0.000

^aThe underlying process assumed is independence (white noise).

^bBased on the asymptotic chi-square approximation.

where U_t is the random disturbance term, P_t is the price of the stock at time t, a_1 is the part of the stock price that does not depend on the previous price of stock (constant term), a_2 is the degree to which is the stock price at time t is dependent on the stock price at time t-1.

In this regression model, to test the randomness of stock price changes, it requires to test H0: $a_2 = 1$, that is, the stock price changes are non-random and statistically dependent at 95% confidence level.

The results presented on the Table 5 also exhibit a significant auto-regression coefficient AR_1 (-0.297) significantly different from zero during the whole sample period. The auto-regression coefficient at first and second lags are significant at 1% level of significance proves that the series are not independent and the returns are predictable. It is important to note that the results are consistent with the auto-correlation tests. However, the null hypothesis that the return series are independent is rejected in this case as well.

In addition to the above statistical techniques, this study runs ARIMA, the dynamic time series model to examine whether the stock return series depends not only on its past values of the return series but also on past and current disturbance terms. ARIMA stands for Auto-regressive Integrated Moving average, including the three components of the general ARMA model.

ARIMA models combine as three types of processes: Auto-regression (AR); differentiating to strip off the integration (I) of the series; and Moving average (MA).

The general model, neglecting seasonality, is written as ARIMA (p, d, q) where p is the order of auto-regression, d is the degree of differencing, and q is the order of moving average involved.

In an auto-regressive process, each value in a series is a linear function of the preceding value or values. That is, in a first order auto-regressive process, only the single preceding value is used; in a second process, the two preceding values are used; and so on. For example; AR(1) is first order auto-regressive process, where,

Value
$$t = \text{disturbance } t + \theta \text{ value } t - 1.$$

For example, in this study,

$$LnP_t = \varepsilon_t + \theta LnP_{t-1} \tag{4.3}$$

We can study an integrated series by looking at the changes or differences from on observation to the next. This type of I (1) process is often called a random

Variables in the model	Coefficients	SEB	T-Ratio	Approx. Prob.
AR1	-0.297	0.127	-2.341**	0.019
LnRmt-1	-0.059	0.021	-2.788*	0.005
LnRmt-2	-0.052	0.021	-2.463**	0.014
CONSTANT	0.002	0.000	6.702*	0.000

Table 5. Results of auto-regression test of the daily return series.

^{*}Denotes significant at 1% level and **denotes significant at 10% level.

walk because each value is a random step away from the previous value. Degree of differencing depends on the non-normality of the data series and also to convert the non-stationary data to a stationary series.

The process uses data on past forecasted errors. Each value in a series is determined by the average of the current or more previous disturbance terms.

I.e., Value
$$t = \text{disturbance } t - \theta^* \text{ disturbance } t - 1.$$

In this study, if it is first order moving average MA (1) is used then the equation will be as follows:

$$LnP_t = \varepsilon_t - \theta \varepsilon_{t-1}, \tag{4.4}$$

where ε is the disturbance term.

This study runs ARIMA, the dynamic time series model to examine whether the stock return series depends not only on its past values of the return series but also on past and current disturbance terms. Theoretically the weak-form efficiency of the market persists when we cannot predict the share prices or returns from its historical price or return information. When the share returns can be predicted on the basis of data on past returns and on forecasted past errors together this gives rise to ARMA model. That is to mean if stock return is a function of it's past values of stock returns itself or the current and past values of the disturbance terms means predictability of returns. This study uses ARIMA model instead of ARMA because it includes the integration process.

Ultimately, ARIMA model is the combination of both Eqs. (4.3) and (4.4) including the differencing of the data series first.

I.e., Ln
$$P_t = f(\operatorname{Ln} P_{t-1}, \dots, n, \varepsilon_{t-1}, \dots, n) \dots$$
 (4.5)

Theoretically the weak-form efficiency of the market persists when we cannot predict the share prices or returns from its historical price or return information. When the share returns can be predicted on the basis of data on past returns and on forecasted past errors together this gives rise to ARMA model.⁶ That is to mean if stock return is a function of it's past values of stock returns itself or the current and past values of the disturbance terms means predictability of returns.

This study uses ARIMA model instead of ARMA because it includes the integration process. As we know that under the random walk model, it needs to fit the model in ARIMA (0,1,0), where the future value of share returns cannot be determined on the basis of past information. Specifically, future share returns will not depend on past (lag) values of share returns or on the past error terms. The significant coefficients of auto-regression (AR) or moving average (MA) different from zero suggest dependency of the series, which violates the assumption of random walk model and weak-form efficiency.

⁶ "If the weak-form efficiency does not hold then actual return $(R_t + 1)$ might not only depend upon past returns but could also depend on past forecast errors." [14, p. 126].

Table 6. Results of ARIMA model [ARIMA (0,1,0), ARIMA (2,0,2), and ARIMA (1,0,0)] for the daily market return series.

	Coefficient	SE	T-ratio	Prob.
ARIMA (0,1,0)				
CONSTANT	-0.0000189	0.000	-0.043	0.966
ARIMA(2,0,2)				
AR1	-0.136	0.020	-6.638*	0.000
AR2	-0.968	0.020	-48.879*	0.000
MA1	-0.126	0.027	-4.732*	0.000
MA2	-0.948	0.025	-37.498*	0.000
CONSTANT	0.002	0.000	6.508*	0.000
ARIMA(1,0,0)				
AR1	-0.186	0.343	-0.541	0.588
CONSTANT	0.002	0.000	6.622*	0.000

^{*}Denotes significant at 1% level.

Results from the Table 6 suggest that the return series of Botswana are not following the random walk model. As we mentioned earlier that ARIMA (0,1,0)supports the random walk model. We at first, calculates ARIMA (0,1,0) of the daily return series for the sample period, where the coefficient is -0.0000189 (0.000) with a t-ratio of -0.043 and probability of 0.966. The diagnostic checking of ARIMA (0, 1, 0) models provides the AIC (Akaike's Information Criteria) -10881.7 and BIC (Schwarz' Bayesian Criteria) -10870.3, and shows significant residual autocorrelation at lags suggest that the model is not well fitted. During the sample period, ARIMA (2,0,2) is found as the best fitted model with AR₁ coefficient (-0.136); AR₂ (-0.968); and MA₁ (-0.126); MA₂ (-0.946) significant at 1% level of significance. The diagnostic checking shows that there is no significant residual auto-correlation in the return series. In addition to the ARIMA (0,1,0) and ARIMA (2,0,2), we also run ARIMA (1,0,0) for whole the sample period to examine whether the auto-regression coefficient (AR1) is equal to one or unity. It should be noted that when the auto-regression coefficient is equal to unity, implies the changes of returns from one period to another period is only due to current disturbance terms. That is the return series do not depend on past information of the return series or past forecasted errors. But the results presented on the Table 6 reports that the coefficient is only -0.186, means that the changes in the return series are not due to the current disturbance terms, which does not support the random-walk model. In short all the evidence suggests that there is a significant dependency of past returns information on the BSE, which is against the weak form efficiency of the market and proves that the past return series can be used to predict the future returns.

The robustness of the results of the study is assessed using different statistical tests and finding the consistency of the results, which eventually increases the reliability of the results. As we know that there are two types of econometric problems faced in this type of research, one is non-normal distribution and another is heteroskedasticity. This study considers the logarithmic returns instead of discrete returns. In addition the study uses both parametric and non-parametric tests, the

latter ignores the distribution to be normal or not. To prevent the heteroskedasticity problems in the OLS regression, the study considers the exact maximum likelihood auto-regression techniques, which is free from this bias. In choosing the best fitted model in ARIMA model, we have considered two main diagnostic checking: firstly, the ACF (auto-correlogram function) of the residual errors accept the null hypothesis that the residuals are white noise (Box–Ljung probability is not significant). Secondly, for a given series with different models the lower AIC (Akaike Information Criterion) and SBC (Schwartz Baysian Criterion) has been considered in selecting the best-fitted model.⁷

However, the results presented in the study do not investigate the aspects of profit-making strategy in detail using any technical trading rules or adjusting transaction cost (such as bid-ask spread, brokerage fee, time lag of settlement procedures) and as a result we can reach no conclusion in this regard. Similarly, using equally weighted indices may bias the results. The problems of non-trading bias have, however, been tried to overcome by considering the actively traded individual company's daily share return series in run test. And the result of individual share returns also evident that the return series are not independent.

Overall empirical findings of the study suggest that the return series on the BSE does not follow random walk model. The frequency distribution of the stock return series on BSE does not exhibit a normal distribution, which is confirmed by the nonparametric K-S normality test. The results of run test and auto-correlation coefficient tests indicate the non-random nature of the series and violate the assumption of the hypothesis that the market is efficient in weak form. Further test on the predictability of past values in the series using dynamic time series statistical techniques such as exact maximum likelihood auto-regression analysis and ARIMA model confirms the previous findings and the results are consistent all over the sample period. The results are quite similar to the findings of [1, 7, 13, 21, 24, 29, 33, 36, 38]. They also find the evidence of non-randomness stock price and return behaviour on the Saudi Arabian Financial market, Kuwaiti market, Indian market, Bangladeshi market, Russain market and other major emerging markets, while at the same time contradicting the findings of [5, 15, 34, 35] who cannot reject the random walk hypothesis on the Kuala Lumpur Stock Exchange, Nairobi Stock Exchange, four Latin American emerging markets, and UAE stock market respectively.

5. Conclusion

Market Efficiency is an area of enormous interest in financial literature. Numerous researchers conducted empirical studies in testing weak-form market efficiency in many countries and employed various techniques but the empirical evidence is controversial. This study mainly seeks evidence of market efficiency and keen to see

⁷AIC = T ln (residual sum of squares) +2n; and SBC = T ln (residual sum of squares) +n ln (T); where T = number of useable observations and n = number of parameters estimates.

whether Botswana Stock Market return series is independent or follows random walk model. Triangulation econometric approach is employed to assess the predictability of daily return series of Botswana Stock Exchange (BSE) and to test the null hypothesis of random walk model. The empirical results reject the null hypothesis of random walk model for the daily return series of BSE for the period of 1989– 2005 and evidenced serial autocorrelation of return series, which clearly indicate predictability and volatility of security prices of Botswana market. However, the empirical evidence of both non-parametric (Kolmogrov-Smirnov: normality test and run test) and parametric test (Auto-correlation test, Auto-regressive model, ARIMA model) reject the hypothesis of random walk model and indeed violate the notion of weak-form market efficiency. Finally, the empirical results of this paper are quite similar to the findings of [1, 7, 13, 21, 24, 29, 33, 36, 38]. They also find the evidence of non-randomness stock price and return behavior on the Saudi Arabian Financial market, Kuwaiti market, Indian market, Bangladeshi market, Russian market and other major emerging markets, while at the same time contradicting the findings of [5, 15, 34, 35] who cannot reject the random walk hypothesis on the Kuala Lumpur Stock Exchange, Nairobi Stock Exchange, four Latin American emerging markets, and UAE stock market respectively. Overall, the findings of this research are interesting and will encourage academic researchers to explore avenues for future research on the stock market like Botswana.

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