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Price Discovery and Memory Effects in Infant African Stock Markets: Evidence from Tanzania

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Abstract

This paper examines the price discovery mechanism at the Dar es Salaam Stock Exchange (DSE) in Tanzania. The objective is to explain the efficiency of price discovery in relation to its dynamics and deterministic market features, using the All Sector Index (ASI). Our results provide evidence of inefficient price discovery at the Exchange, associated with some moments of structural shifts. Moreover, the inefficient price discovery is corroborated by the fact that the Index does not follow a random walk. These finding are consistent with our investigation of the main features of the market: inactive trading, illiquidity, high dependence on foreign investors to boost market activities, investors' dependence on dividend as the main source of income rather than stock trading, uncompetitive trading among brokers, and motives for more returns from alternative portfolio investments in government securities. Generally, the findings have strong implications for market participants and policy makers at the DSE and similar markets.

Keywords: Africa, infant stock markets, market features, price discovery, random walk, Tanzania

1. Introduction

One of the core functions of stock markets is to facilitate price discovery (DSE Handbook, 2010), in which market forces, through interactions between buyers and sellers, determine stock prices. Theoretically, price discovery is expected to be a dynamic process, characterized by a fast equilibrium adjustment mechanism in which the arrival of information drives prices into that equilibrium (see Schreiber & Schwartz, 1986; Baillie, Booth, Tse, & Zabotina, 2002; Lehmann, 2002). Essentially, the dynamics of price discovery for an asset depends on several factors such as: the market characteristics like transaction costs and liquidity (O'Hara, 2003); the speed and frequency of trading activities (Brogaard, Hendershott, & Riordan, 2012); the institutional structure of the market; alternative trading venues; and alternative investment opportunities (Hasbouck, 1995).

In essence, market discovery can be elaborated by the traditional financial theories of market efficiency and random walk (Dharmanesa & Bessler, 2004), which can be understood through examining the distribution and memory effects of asset prices. On Tanzania, the literature does not offer evidence on the distribution of stock returns at the only stock exchange (DSE) in relation to its stock index structure. However, some news headlines can be a good starting point to understand the main features of the DSE. Table 1 summarizes some of the common news headlines, from which it is possible to deduce the following characteristic features: inactive trading, investors' dependence on dividend as the main source of income rather than stock trading, uncompetitive trading among brokers, high dependence on foreign investors to boost market activities, a few number of actively traded stocks, and illiquidity. Although there is no empirical evidence to affirm these characteristic features, they roughly signify market inefficiency.

In finance, the understanding of stock market behaviors has been made possible through different approaches. The Efficient Market Hypothesis (EMH) is one of the fundamental explanations of market behavior. Formalized by Fama (1965), the EMH technically states that the market is a martingale (fair game); hence information cannot be used to make profits. The cardinal philosophy of EMH is that all assets are priced so that all public information, both fundamental and price history, is already discounted in the prevailing market prices (Fama, 1970). Therefore, the only driver of price movements is new information or event. It follows that, if the market is efficient (prices carry all the information), no one is able to outperform it by market gaming because all investors are assumed to be rational and will ensure that the prices are fair. Investors, thus, make decisions after digesting the information and assessing the risks involved. Consequently, their collective consciousness of the market ensures equilibrium in the pricing mechanism. The theoretical explanation of equilibrium is that only today's information is important in making changes in today's prices. That is, today's prices are not related to yesterday's prices.

If stock prices are independent, they should follow a random walk and become unpredictable (Fama, 1998). Consequently, a normal probability distribution is achieved if there is enough collection of independent price changes, as the number of observations approaches infinity. From this normality assumption, emerges a large spectrum of statistical approaches to analyze asset price behavior, including the random walk version of the EMH. However, it is important to emphasize on the antagonistic implications of the two price behaviors: that is, market efficiency does not necessarily imply a random walk, but a random walk implies market efficiency. Hence, efficient markets do not necessarily guarantee normality of return distribution.

Further theoretical assertions categorize market efficiency into three categories: weak form, strong form and semi-strong form (Lorie & Hamilton, 1973). These forms provide a more practical explanation for the drivers of randomness. The strong form asserts that prices already reflected "all that is knowable", or all public and private (insider) information. The weak form postulates that prices reflect only past price histories. Therefore, market efficiency is explained by the historical independence of prices, which may follow a random walk. Semi-strong form posits that prices only reflect public information. Therefore, it suggests that price randomness is not caused by the price series itself, but by outside influences such as security analysts. Hence, markets are said to be efficient simply because their prices reflect all public information.

The random pricing process can also be linked to some deterministic processes in a security market. This linkage is explained by a phenomenon referred to as chaos (Baren, 1994; Campbell, Lo, & MacKinlay, 1997). In a deterministic system, chaotic dynamics can amplify small changes, thereby producing unpredictable behaviors in long run. Thus, whereas it is almost impossible to make long-term prediction, it is possible to make accurate short-term predictions. Hence, chaos has both good and bad implications for the prediction problem. The ability to predict the future is an important input for all decision makers in security markets. Conventionally, the ability to predict is a function of availability of information and prediction techniques. This conventional position is contradicting the chaos theory, which considers unpredictability as an inherent attribute of a wide range of phenomena. Hence, predicting is regarded as a fruitless exercise because it would be impossible to know and monitor all the variations that might have a significant effect on price changes.

Table 1. Characteristic features of the Dar es Salaam stock exchange

Headline	News Media	Main Issue (Reporter)
Cross-listed shares seem dormant at Dar Bourse	Daily News	Cross-listed shares at DSE are hardly traded because they are properly prices at home and there is lack of communication (Elinaza, 2013)
TBL, CRDB Bank shine as foreign funds flow via DSE	Business Times	About 93 per cent of TBL and 67 per cent of CRDB turnovers and activities were based on foreign investors´ support during the trading week (Chiwango, 2012).
Stockbrokers Blamed for Creating 'Fake' Liquidity	Daily News	The Capital Markets and Securities Authorities (CMSA) blames stockbrokers for 'creating artificial liquidity by posting shares on the "all or none" board thus preventing locals from buying even a fraction of such stocks (Elinaza, 2012).
Stockbrokers Push for Law Review	Daily News	Stockbrokers are pushing for a review of laws that ban local investors to sell shares to foreigners from a company, with 60 per cent overseas ownership (Elinaza, 2012).
Dar es Salaam Bourse Records Low Trade On Flat Counters	Daily News	Overall drop of market activities as most counters either remained flat or lost their values during the specified week. Improvement of the activity levels was caused by the sale of TATEPA (TTP) shares to foreign investors in a pre-arranged deal (Elinaza, 2012).
Dividends Push Up Dar es Salaam Bourse Trade	Daily News	DSE trading activities were set to increase as the bourse enters into the season of annual dividends. Traditionally, most DSE's investors tend to target dividends as their main investment returns instead of capitalising by buying and selling when share prices fluctuates (Elinaza, 2012).
Banks Shine At Dar es Salaam Bourse	Daily News	Listed Banks became the most liquid stocks in the trading sessions of the week with NMB contributing about 70.12 per cent per cent of the total market turnover (Mrindoko, 2012).
Trading to Pick Up On DSE As	Daily News	Trading on the DSE was expected to pick up as yields from fixed income

Yields On T-Bills Dwindle		securities and money market instruments kept on falling. Previously investors eyed risk free government securities that offered lucrative yields of between 13 per cent and 18 per cent. On average stocks' dividend yields per year is around 10 per cent (Elinaza, 2012e).
CRDB Bank shares most traded at DSE	Daily News	Analysts comment that CRDB shares provide a lifeline to DSE trading activities as most of stocks appear to struggle (Elinaza, 2011).
How CRDB Shares Provide a Lifeline to DSE Trading Activities	The Citizen	CRDB shares provided a lifeline to DSE trading activities as most of stocks appeared to struggle (Rutabingwa, 2011).
As Govt. Paper Gains Momentum: Equity Market Trading Continues To Be Sluggish	Business Times	Trading activities at DSE continued to be sluggish due to a number of factors, including: (1) investors preferring government securities which offer higher returns and considered to be risk-free; (2) the Initial Public Offer (IPO) by TBL for shares owned by the EABL (Chiwambo, 2011).
Depreciating shilling, power outages slow down activity at Dar stock mart	Business Times	The relentlessly weakening Tanzania shilling, surging inflation and persisting acute electricity rationing are among the reasons for continuing sluggishness in activities of the DSE (Chiwambo, 2011)
Foreign investors restore life to DSE trading	Business Times	After several weeks of absence of foreign investor activity at the DSE, foreign players were back with a vengeance, to bring life to the exchange (Chiwambo, 2011)
Capital markets sluggish as macroeconomic indicators sour	Business Times	Investor-appetite for equities and government securities in Tanzania waned in the first week of the new 2011/12 financial year, largely due to macroeconomic concerns: inflation, weakening Shilling, power energy problem, and high interest rates (Business Times, 2011)
Eight-in-ten investors in equity are largely uninformed	Business Times	Only 20 per cent of Tanzanians seriously consider information on firms before purchasing shares at the Dar es Salaam Stock Exchange (DSE), according to a study by Dr. Norman Sigalla (Chuwa, 2011).
Foreign buyers crowding out locals from DSE shares sales	Business Times	Levels of local ownership of shares at the DSE were shrinking day after day, as a result of increasing share purchases by foreign investors – mainly in the banking sub-sector (Business Times, 2011).
DSE trading slows as investors hold shares	Business Times	Share trading at the DSE slowed due to low share supplies (Mbani, 2011).

It follows that market efficiency, random walk, and predictability are related financial aspects, useful in explaining memory effects in security markets. Long memory means slow price discovery and market inefficiency, characterized with persistent prices and periodic cycles. Short memory is the contrary. This paper, therefore, analyzes these issues in the context of the DSE. The need to study the Tanzania stock market is substantiated with two main contributions. Firstly, there is a limited literature on infant stock markets, especially African markets. Several reasons are usually mentioned for lack of interest in studying infant African markets such as: lack of sufficient data, the smallness and newness of the markets, land lack of integration and visibility to external markets. However, these reasons are unjustifiable because knowledge on infant stock market is as important as knowledge in advanced markets: regardless of their context, size and proximity to other markets. This study, therefore, endeavors to narrow the existing wide knowledge gap on African stock markets. Secondly, the study contributes in providing empirical evidence on characteristic features of the DSE, thereby aiding investors and other stakeholders in making informed decisions. Overall, the study attempts to explain whether or not price discovery, one of the core functions of stock markets, can be achieved in infant markets like the DSE.

There are several financial forecasting approaches like Autoregressive Conditional Heteroskedasticity (ARCH-type) models (Engle, 1982; Bollerslev, 1986), Vector Error Correction Models (Johansen, 1988, 1991) and so on. In this study we apply simple tests for stock return distribution and memory effects. The aim is to use the dynamic features of the DSE stock index and the deterministic features of the market to explain the efficiency of the price discovery mechanism. Specifically, we analyze the distribution of the index in relation to serial correlation, heteroskedasticity and normality as well as measuring for unit root and random walk. Overall our results suggest that the price discovery mechanism at DSE is inefficient, alongside strong evidence of non-normality and stationarity. Moreover, the index appears to exhibit structural shifts, mainly associated with stock listings.

The remainder of the paper is organized as follows. Section 2 describes the modeling approach for memory effects in the price discovery mechanism, while section 3 describes the DSE stock index and data properties. Section 4 presents empirical results and discussions on memory effects, whereas section 5 provides an overall conclusion.

2. Modeling Memory Effects in the Pricing Mechanism

Consider a discrete time stochastic process as $P_t = (P_1, P_2, P_3 \ldots P_T)$, where P_t is the natural logarithm of either the stock price or return observed at trading days, and T is the number of observations. This process can be modeled as an autoregressive process of order p as:

$$P_t = c + \alpha_1 P_{t-1} + \alpha_2 P_{t-2} \ldots + \alpha_p P_{t-p} + \varepsilon_t \tag{1}$$

$$\varepsilon_t \setminus \Omega_{t-1} \approx N(0, \sigma^2) \tag{2}$$

ε_t is the random error term assumed to be normally distributed, with mean zero and constant variance σ^2, upon a previous set of information Ω_{t-1}. If the coefficient α is statistically significant, today's prices depend on yesterday's prices. This stochastic process can be used to test for memory, by using a simple unit root test. For a first order autoregressive process (p =1), there is unit root when α_1 = 1. For a higher orders of p, the process has a unit root when $\sum(\alpha_1 + \alpha_2 + \alpha_p) = 1$. Unit root means the time series is nonstationary and the moment of the stochastic process depends on time (t).

Moreover, it is the random error term that explains whether or not the current prices reflect previous set of information. Thus, residual serial correlation can provide a further measure of the relationship between current prices and information. We consider the popular Lagrange multiplier (LM) test for large samples (see Godfrey, 1988). LM tests the null hypothesis that there is no serial correlation in residuals up to a specified lag order (p). This is the advantage of LM over other tests like Durbin Watson, which are unable to capture serial correlation in higher orders. The LM test is based on auxiliary regression because ε_t is unobservable. From equation (1) an auxiliary error term (e) can be expressed as,

$$e_t = \gamma P_{t-1} + \left(\sum_{s=1}^{p} \phi_s e_{t-s} \right) + v_t \tag{3}$$

Further, we can test for heteroskedasticity in the residuals, using ARCH-LM test (Engle, 1982). This test is based on the null hypothesis that there is no ARCH up to lag order q in residuals (e). It is based on regressing the squared residuals on a constant and lagged squared residuals, as follows:

$$e_t^2 = \alpha_0 + \left(\sum_{s=1}^{q} \alpha_s e_{t-s}^2 \right) + v_t \tag{4}$$

In both tests (LM serial correlation and ARCH-LM), the respective null hypotheses are rejected by the statistical significance of the *F-statistics* on an OLS regression, with observations (T) and numbers of dependent variables (k). Thus,

$$F = \frac{R^2 / (k-1)}{(1-R^2)/(T-k)} \tag{5}$$

$$\text{where, } R^2 = 1 - \frac{\widehat{\varepsilon}'\widehat{\varepsilon}}{(P - \widehat{P}'(P - \widehat{P})}; \quad \widehat{P} = \sum_{t=1}^{T} P_t / T \tag{6}$$

$$\text{and } \widehat{\varepsilon}'\widehat{\varepsilon} = \sum_{t=1}^{T} (P_t - \alpha P_{t-1})^2; \quad \widehat{\varepsilon} = P_t - \alpha P_{t-1} \tag{7}$$

To test random walk, suppose the time series P_t, satisfies,

$$\Delta P_t = \mu + \varepsilon_t \tag{8}$$

where μ is an arbitrary drift parameter. The key properties of a random walk to be tested are from expectations (E), such that $E(\varepsilon_t) = 0$ for all t and $E(\varepsilon_t \varepsilon_{t-j}) = 0$ for any positive j. From Lo and MacKinlay (1988), random walk tests can be performed using two test statistics under different sets of null hypothesis assumption about the random error (ε_t). The first test is referred to as *homoscedasticity* random walk, in which ε_t is assumed to be normally distributed (Gaussian) with variance σ^2. The second set is called *heteroskedastic* random walk, which relaxes the common normality assumption and provide for fairly general forms of conditional heteroskedasticity and dependence.

The estimators for the mean and first difference and scaled variance of the q-th difference can be defined as,

$$\widehat{\mu} = \frac{1}{T}\sum_{t=1}^{T}(P_t - P_{t-1}) \tag{9}$$

$$\widehat{\sigma}^2(q) = \frac{1}{Tq}\sum_{t=1}^{T}(P_t - P_{t-1} - q\widehat{\mu})^2 \tag{10}$$

In order to adjust for bias, T in equation (9) and (10) can be replaced with (T-q+1) or (T-q+1)(1-q/T) for a non-drift and with-drift cases, respectively. The corresponding variance ratio (VR) is defined as,

$$VR(q) = \widehat{\sigma}^2(q) / \widehat{\sigma}^2(1) \tag{11}$$

The test statistic (z) for variance ratio is asymptotically $N(0,1)$ for appropriate choice of estimator $\left[\widehat{s}^2(q)\right]$, such that,

$$z(q) = \left(VR(q) - 1\right)\left[\widehat{s}^2(q)\right]^{-1/2}; \quad s = \sqrt{\frac{\widehat{\varepsilon}'\widehat{\varepsilon}}{(T-k)}} = \text{Standard error} \tag{12}$$

Thus, the estimator for the normality assumption is,

$$\widehat{s}^2(q) = \frac{2(2q-1)(q-1)}{3qT} \tag{13}$$

While the relaxation of normality leads into a kernel estimator,

$$\widehat{s}^2(q) = \sum_{j=1}^{q-1}\left(\frac{2(q-j)}{q}\right)^2 \widehat{\delta}_j \tag{14}$$

$$\text{where, } \widehat{\delta}_j = \left\{\sum_{t=j+1}^{T}(p_{t-j} - \widehat{\mu})^2 (p_t - \widehat{\mu})^2\right\} / \left\{\sum_{t=j+1}^{T}(p_{t-j} - \widehat{\mu})^2\right\}^2 \tag{15}$$

Following Chow and Denning (1993), joint variance ratio tests are enabled by restricting $p > 1$. Further details on empirical application are available in Fong, Koh and Ouliaris (1997). Moreover, Kim (2006) offers an improved approach (wild bootstrap) for testing both individual variance ratio and joint variance ratio.

3. Data and the DSE Stock Index Structure

3.1 Data and Descriptive Statistics

The DSE categorizes its indices into different classes namely: All Share Index (ASI), Tanzania Share Index (TSI), Foreign Share Index (FSI), Industrial and Allied Share Index (ISI), Banking and Insurance Share Index (BSI) and Commercial Services Share Index (CSI).

Table 2. DSE listed stocks

SN	Stocks	Base	Industry	Date Listed#
1	Tol Gases Limited (TOL)	Tanzania	Energy	04/15/1998
2	Tanzania Breweries Limited (TBL)	Tanzania	Brewers	09/09/1998
3	Tanzania Tea Parkers Limited (TATEPA)	Tanzania	Beverage	12/191999
4	Tanzania Cigarette Company Limited (TCC)	Tanzania	Cigarette	11/16/2000
5	Tanga Cement Company Limited (SIMBA)	Tanzania	Cement	09/26/2002
6	Swissport Tanzania Limited (Swiss)	Tanzania	Aviation	06/03/2003
7	Kenya Airways Limited (KA)	Kenya	Aviation	10/01/2004
8	East African Breweries Limited (EABL)	Kenya	Brewers	06/29/2005
9	Tanzania Portland Cement Co. Limited (TWIGA)	Tanzania	Cement	09/26/2006
10	Jubilee Holdings Limited (JHL)	Tanzania	Insurance	12/20/2006
11	Dar es Salaam Community Bank (DCB)	Tanzania	Banking	09/16/2008
12	National Microfinance Bank (NMB)	Tanzania	Banking	11/06/2008
13	Kenya Commercial Bank Limited (KCB)	Kenya	Banking	12/17/2008
14	CRDB Bank Public Limited (CRDB)	Tanzania	Banking	06/17/2009
15	National Media Group Limited (NMG)	Kenya	Media	02/21/2011
16	African Barrick Gold Plc (ABG)	United Kingdom	Mining	12/07/2011
17	Precision Air Services Plc (PAL)	Tanzania	Aviation	12/21/2011

Note. #In the entire paper, dates follow the sequence MM/DD/YYYY. That is Month/Date/Year.

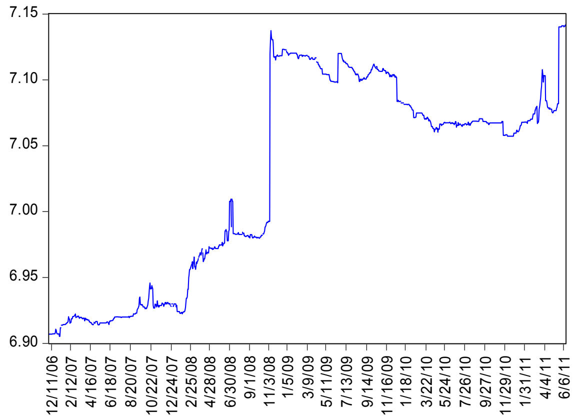
This study uses the ASI in order to capture information about the entire market, comprised of seventeen listed stocks (see Table 2). The ASI data was obtained from DSE (upon request) spanning from December 1st 2006 to June 13th 2011, covering 1125 observations of trading days. Stock price indices at DSE are reported in Tanzanian Shillings (TZS) per share on a particular trading day. For analysis purposes, we transform the TZS series it into natural logs, in which the first log difference defines stock index returns.

Table 3. Descriptive statistics and normality

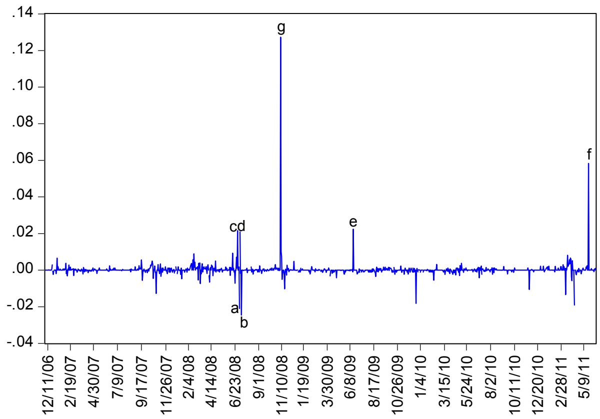
		Mean	Std. Deviation	Skewness	Kurtosis	Jarque-Bera
Whole	TZS (level)	1129.5090	86.3777	-0.2510	1.4543	123.8013 (0.000)
	Log (level)	7.0266	0.0775	-0.2953	1.4618	127.2535 (0.000)
	Log (difference)	0.0002	0.0048	18.5458	478.0567	106.3337 (0.000)
Sub-sample 1	TZS (level)	1125.1590	87.3257	-0.1836	1.3748	55.6412 (0.000)
	Log (level)	7.0212	0.0778	-0.1346	1.3906	53.3631 (0.000)
	Log (difference)	0.00005	0.0023	-0.9761	52.9746	503.6600 (0.000)
Sub-sample 2	TZS (level)	1134.427	86.9591	-0.3677	1.5061	74.3960 (0.000)
	Log (level)	7.0266	0.0761	-0.2787	1.4607	71.9181 (0.000)
	Log (difference)	0.0002	0.0030	1.8086	36.9110	311.5900 (0.000)

Note. Numbers in parentheses are p-values.

Table 3 presents descriptive statistics and normality distribution of the index. From the Jarque-Bera test, there is strong evidence of non-normality in the index series. Regarding skeweness, the index (levels) appears to be left-skewed, while the returns are right-skewed (except in sub-sample 1). Left-skeweness implies a greater chance of extremely negative outcomes as well as asymmetry, whereas the right-skeweness in returns implies minimal losses to investors during the covered period. Kurtosis for the index appears to be normal (below the accepted level of 3). However, returns exhibit extremely high kurtosis, suggesting the moments of very low and very high returns than expected. These distribution features are clearly envisaged in Figures 1 to 3.

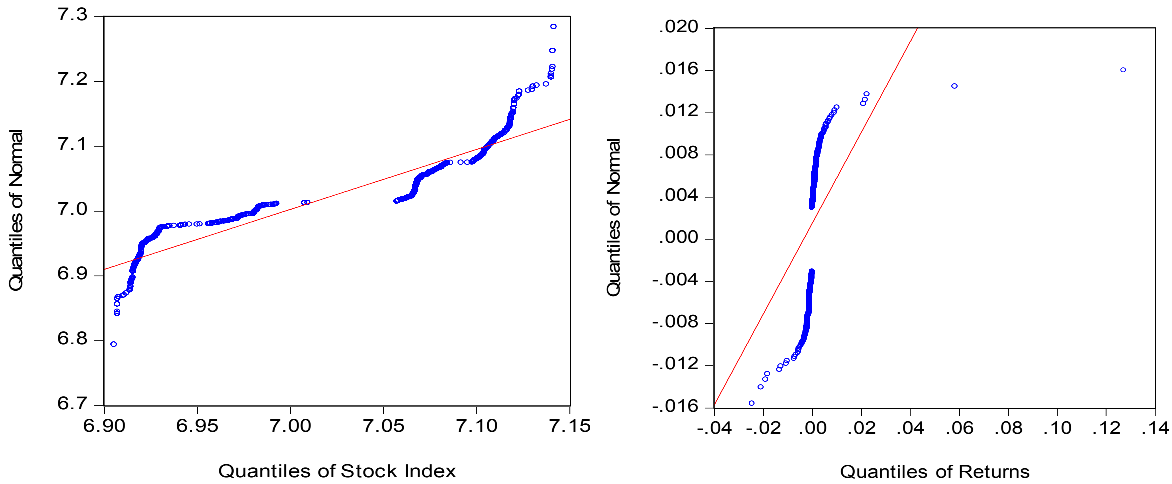


(i) Log Level



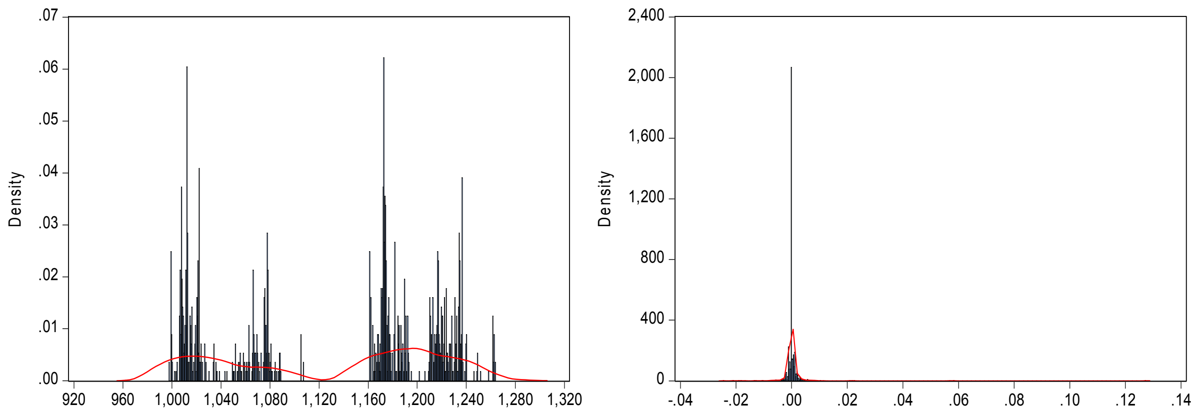
(ii) Returns

Figure 1. Index structure (December 1st 2006 to June 13th 2011)



(i) Log level (ii) Returns

Figure 2. Quantiles of normal



(i) Log level (ii) Returns

Figure 3. Index distribution density

Figure 1 depicts the series structure of the ASI (log levels) and returns (log differences). There is a clear evidence of a structural shift in November 6th 2008. In Figure 1(ii), the index returns are characterized by remarkable outliers (abnormal or unexpected returns), whose points are marked a to g. These points correspond to certain market events identified in Table 4 (together with cross tabulation): points a (July 4th 2008) and b (July 11th 2008) coincides with activities to delist the National Investment Company (NICOL) after a one-month suspension in June 2008. NICOL was delisted effectively from July 6th 2008 due to failure to comply with financial statement disclosure requirements. July 4th and 11th 2008 were Fridays before and after the effective delisting, respectively. The outliers in both points indicate loss of returns of almost 2 percent, on average. Our efforts to identify any event on point c (June 30th 2008) and point d (July 8th 2008) were unsuccessful. Point e (June 17th 2009) is the CDRB listing date in which the market return was about 2 percent, while point f (May 23rd 2011) corresponds to CRDB's dividend activities. On this date point, the market return was about 6 percent, which was just a day before trading of shares cum-dividend at the bank. During the corresponding period CRDB made key announcements about dividend payment as follows: Announcement of dividend payment (May 5th 2011), trading of shares cum-dividend (May 5th 2011 to May 24th 2011), and trading of shares ex-dividend (May 25th 2011 onwards), among other announcements. Date point g coincides with NMB listing date, leading to a return of about 13 percent.

Figure 2 provides a better view of distribution in the index and returns, using quantiles of normal. Clearly, the quantiles of normal do not lie in the diagonal straight lines, suggesting that mainly positive shocks drive the index from normality, while both positive and negative shocks equally drive the returns from normality. Moreover, the quantiles appear to be separated into two parts, thereby providing a further evidence of a structural break. The histograms and distribution density in Figure 3 confirm skeweness in the index. From Table 4, we also see that 75 percent of the returns (843 observations) are between 0 and 2 percent, while about 24 percent (274 observations) are losses of between 0 and 2 percent. The overall interpretation is that investors are not expected to have any gains or losses of more than 2 percent. Any gain or loss of more than 2 percent is regarded as abnormal (unexpected). Indeed, these abnormal earnings or losses appear to be very rare (and as evidenced in the right-skeweness and excess kurtosis).

Table 4. Tabulation of index returns

Value	Count	Percent	Outlier Dates	Outlier Values
-0.04 to -0.02	2	0.18	[a]07/04/2008, [b]07/11/2008	-0.021, -0.025
-0.02 to 0	274	24.38		
0 to 0.02	843	75.00		
0.02 to 0.04	3	0.27	[c]06/30/2008, [d]07/08/2008, [e]06/17/2009	0.021, 0.021, 0.022
0.04 to 0.06	1	0.09	[f]05/23/2011	0.058
0.12 to 0.14	1	0.09	[g]11/06/2008	0.127

Note. [a,b] The period from July 4th to 11th coincide with activities to delist the National Investment Company (NICOL).

[c,d] Unable to define corresponding events.

[e,f] The periods coincide with CRDB listing and dividend announcements, respectively.

[g] The periods coincide with NMB stock listing dates.

This small market return is probably a reason for investors' more preference in dividend income than stock trading income (see Table 1). On average, DSE investors expect a dividend yield of about 10 percent annually. Comparing with alternative investment in government securities, the overall returns from stock portfolio investments (from both share trading and dividend) are lower. Government securities provide yields of between 13 and 18 percent on average. This may explain the tendency of inactive trading at the DSE floor in most times as investors are attracted by more lucrative earnings in Treasury bond portfolios.

3.2 Structural Shift

It is important to confirm the vivid structural shift, which is evident in November 6th 2008, and test for any possibility of other breakpoints in the DSE index. Since, it is not easy to identify most of the breakpoints with an eyeball of the graphs, we apply a combination of methods developed by Chow (1960), Quandt (1960), Andrews (1993). The Chow approach is based on parameter equality of two sub-samples of the estimated data series. Its limitation is that the breakpoint to be tested must be known in prior. In our case, we assume the known breakpoint to be November 6th 2008, which becomes a point for separating the data series into two sub-samples. Sub-sample 1 is truncated to November 5th 2008, while sub-sample 2 spans from November 6th 2008 onwards. The Quandt-Andrews approach is more general because it does not require any prior knowledge about breakpoints. For further details about the applications and limitations of these tests refer to Hansen (2001).

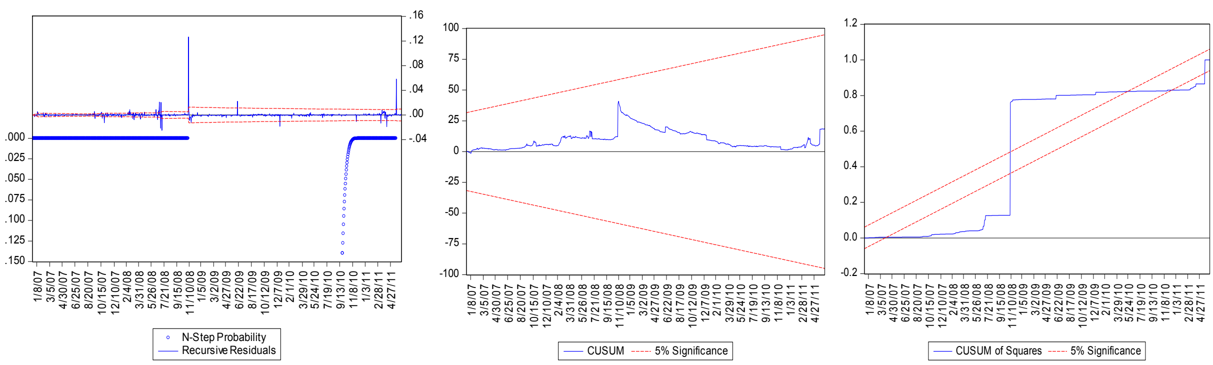


Figure 4. Parameter stability and breakpoint identification: whole sample

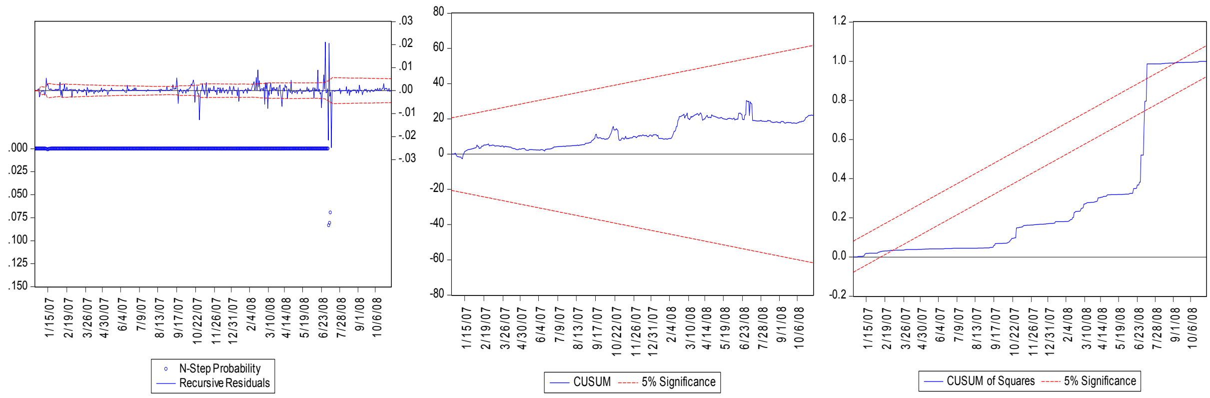


Figure 5. Parameter stability and breakpoint identification: sub-sample 1

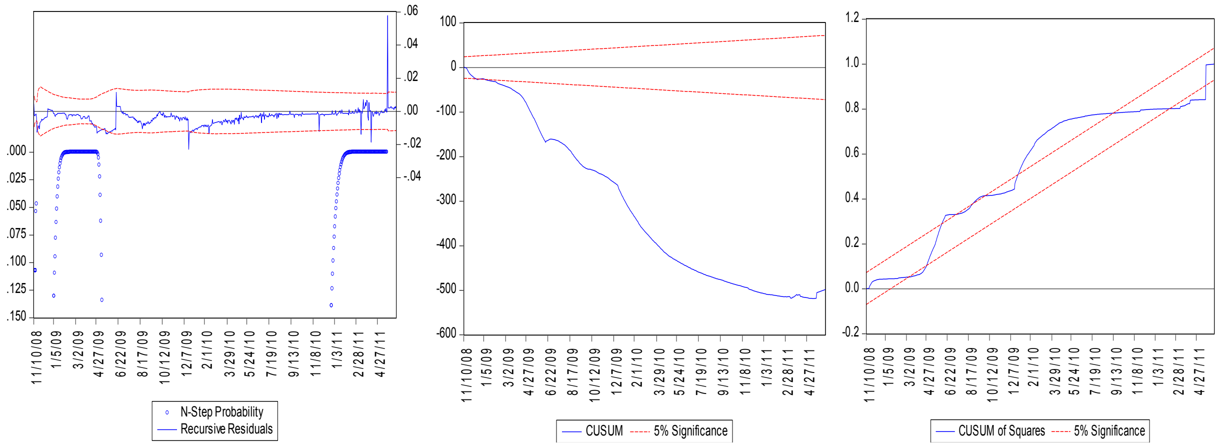


Figure 6. Parameter stability and breakpoint identification: sub-sample 2

The first step for running breakpoint tests is to estimate an OLS autoregressive (AR) regression in the series for each sample. The second step is to conduct stability tests on the estimated residuals for identifying breakpoint using corroborative graphs for residual tests (see Figure 4 to 6). These graphs not only help to check parameter stability, but also provide a general view on any possible breakpoint that could be assumed as known breaks for Chow tests. The first graph (left side) shows a joint plot of recursive residuals and N-step probabilities. The recursive residuals are based on a one-step ahead forecast error resulting from a prediction process of least square estimations of subsets of sample data. If the recursive residuals are independently and normally distributed with zero mean and constant variance, the estimated parameters are assumed to be stable. The resultant graphs show the recursive residuals about the zero line, and plus and minus two standard errors at each point. Residuals outside the standard error bands would suggest instability in the parameters of the equation and a possibility of a breakpoint. The N-step probabilities show the statistical significance of the recursive residuals from a sequence of Chow Forecast tests using recursive calculations. Constant and statistically significant probabilities would suggest a stable period during the sample, while a break and insignificant probabilities suggest a possibility of structural shifts.

The other two graphs show Cumulative Sum of the recursive residuals (CUSUM) and the Cumulative Sum of Squares (CUSUM-SQ) following Brown, Durbin, and Evans (1975). The CUSUM (middle) are plotted together with the 5 percent critical lines. The CUSUM-SQ test is based on a test statistic (S), positing a constant parameter around expected values. The significance of the departure of S from its expected value is assessed by reference to a pair of parallel straight lines around the expected value. In the CUSUM-SQ plots (right side), S is plotted against time and the pair of 5 percent critical lines. In both CUSUM and CUSUM-SQ, a movement outside the critical lines suggests parameter or variance instability, and a sharp departure from the zero horizontal axes would suggest a possible breakpoint.

Finally, we apply the Chow and Quandt-Andrews approaches. For Chow tests, we test the entire sample, taking November 6th 2008 as known shift points. For sub-samples, based on parameter stability plots we assume breakpoints on June 26th 2008 and July 11th 2008 for sub-sample 1, while June 17th 2009 (CRDB listing) is tested for sub-sample 2. For the Quandt-Andrews approach we acknowledge the fact that structural shift tests tend to be sensitive to sample sizes or number of observations (see for example, Inclan & Tiao, 1994; Smith, 2008). Therefore, we do not only test the whole sample, but also each sub-sample is tested separately for any unknown breakpoints.

Table 5. Structural shift tests

	Statistic	Chow Test (Known Shift)	Quandt-Andrews Test (Unknown Shift)
Whole Sample	F-statistics	[a]12.6130***	[a]13.0204***
		(0.000)	(0.000)
	Log likelihood ratio	[a]25.0351***	
		(0.000)	
	Wald statistic	[a]25.2259***	[a]26.0409***
		(0.000)	(0.000)
Sub-sample 1	F-statistics	[b]42.4312***	[c]29.2127***
		(0.000)	(0.000)
	Log likelihood ratio	[b]146.9108***	
		(0.000)	
	Wald statistic	[b]169.7249***	[c]58.4253***
		(0.000)	(0.000)
Sub-sample 2	F-statistics	[d]233.3575***	[e]676.6985***
		(0.000)	(0.000)
	Log likelihood ratio	[d]352.7080***	
		(0.000)	
	Wald statistic	[d]466.7150***	[e]1353.397***
		(0.000)	(0.000)

Note. In Quandt-Andrews, shift points are identified with maximum LR F-statistic and maximum Wald F-statistic, whose probabilities are calculated using Hansen's (1997) approach.

Breakpoints: [a]6th November 2008, [b]26th June 2008 and 11th July 2008, [c]4th June 2008, [d]17th June 2009, [e]1st April 2009.

*** Statistically significant at 1% level. Numbers in parentheses are p-values of the respective test statistics.

Technically, both approaches use two test statistics: the F-statistic, which is based on the comparison of the restricted and unrestricted sum of squared residuals from the estimated OLS equations; and the Wald statistic. In the Chow approach, the Log Likelihood Ratio statistic, which is based on the comparison of the restricted and unrestricted maximum of the (Gaussian) log likelihood function, is used in addition. The presence of breakpoints is suggested by a statistical significance of each of the test statistics. Our results for structural breakpoints are reported in Table 5. The tests indicate a high statistical significance of 1 percent level. Overall, the identified shift points are consistent with our identifications from stability tests. Some of them coincide with stock listing dates for NMB and CRDB, thereby providing a view of the validity of the tests.

4. Estimated Results

Our baseline estimations are based on a simple autoregressive process with OLS. Due to structural breaks identified above, all processes are estimated for three samples (whole, sub-sample 1 and sub-sample 2) in order to enable inference of the impact of the main structural break of November 6th 2008.

Firstly, we run a set of autoregressive processes on equation (1) in order to determine unit root properties. For each sample, the order of the best stochastic process is determined by applying information four filtering technics: Log Likelihood (LL), Akaike Information Criteria (AIC), Schwartz Information Criteria (SIC), and Hannan-Quinn Information Criteria (HQIC). The best autoregressive process is selected for processes with either the largest values of L and smallest values of AIC, SIC and HQIC. Where LL provided contradicting outcomes, our order process is based on AIC, SIC and HQIC. The selection process starts with estimating four processes for each sample, with orders 1 to 4. The information filters for the corresponding estimates are reported in Table 6. Hence, our final selections were order 1 for whole and sub-sample 2, and order 3 for sub-sample 1.

Table 6. Selection criteria for order processes

		Order 1	Order 2	Order 3	Order 4
Whole	LL	**4413.332**	4410.472	4407.252	4402.828
	AIC	-7.8581	**-7.8582**	-7.8577	-7.8550
	SIC	**-7.8536**	-7.8493	-7.8442	-7.8371
	HQIC	**-7.8564**	-7-8549	-7.8534	-7.8483
Sub-sample 1	LL	**2174.170**	2172.216	2173.883	2168.855
	AIC	-9.0738	-9.0804	**-9.1022**	-9.0960
	SIC	-9.0651	-9.0630	**-9.0760**	-9.0610
	HQIC	-9.0704	-9.0735	**-9.0919**	-9.0822
Sub-sample 2	LL	2396.854	2397.355	2397.565	**2397.566**
	AIC	**-7.4405**	-7.4390	-7.4365	-7.4334
	SIC	**-7.4336**	-7.4251	-7.4157	-7.4057
	HQIC	**-7.4378**	-7.4336	-7.4285	-7.4227

Note. The bolded numbers are the most preferable lag orders in different samples.

Table 7. OLS autoregressive estimates

		α1	α2	α3	R2
Whole	Log level	1.0000***			0.9962
		(0.000)			
	Returns	0.0407			-0.0003
		(0.173)			
Sub-sample 1	Log level	0.8790***	0.2288***	-0.1078**	0.9919
		(0.000)	(0.000)	(0.019)	
	Returns	-0.0967**	0.0940**	-0.1665***	0.0521
		(0.033)	(0.039)	(0.000)	
Sub-sample 2	Log level	1.0000***			0.9351
		(0.000)			
	Returns	0.0658*			0.0028
		(0.095)			

Note. ***, **, *Statistically significant at 1%, 5%, and 10% level, respectively. Numbers in parentheses are F-statistics.

The results for the estimated stochastic autoregressive processes are reported in Table 7. For the index (Log levels), α_1 = 1 for the whole and sub-sample 2, while $\sum(\alpha_1+\alpha_2+\alpha_3)= 1$ for sub-sample 1. The coefficients are statistically significant at 1 percent, suggesting that the current stock prices fully depend on previous prices, indicating long memory effects. Moreover, from the R^2, more than 90 percent of the current prices are explained by previous prices. This effect disappears in stock returns, in which almost none of the current returns are explained by previous returns.

Table 8. Unit root tests

		With Constant		With Constant + Trend	
		Log	ΔLog	Log	ΔLog
Whole	Augmented Dickey Fuller (ADF)	-1.069	-32.206***	-1.743	-32.191***
	Phillips-Perron (PP)	-1.115	-32.226***	-1.836	-32.211***
Sub-sample 1	Augmented Dickey Fuller (ADF)	-20.935***	-11.082***	-21.123***	-14.067***
	Phillips-Perron (PP)	-21.197***	-122.399***	-21.242***	-122.182***
Sub-sample 2	Augmented Dickey Fuller (ADF)	-26.066***	-14.667***	-26.049***	-14.654***
	Phillips-Perron (PP)	-26.065***	-245.996***	-26.048***	-246.122***

Note. ***, **, *Statistically significant at 1%, 5%, and 10% level, respectively.

ADF and PP MacKinnon Critical values (with constant): 1% = -3.440; 5% = -2.870; 10% = -2.570.

ADF and PP MacKinnon Critical values (with constant + trend): 1% = -3.966; 5% = -3.414; 10% = -3.129.

However, to corroborate the tests in Table 7, we proceed applying two advanced techniques for unit root test: Augmented Dickey Fuller (ADF) and Phillip-Perron (PP). For discussion and applications of these approaches refer to previous studies (e.g. Perron, 1986; Wang, 2003; Dionisio, Menezes, & Mendes, 2007). The results are reported in Table 8. For the sub-samples, the tests suggest stationary in both index levels and returns. In the whole sample, the index levels are non-stationary while the returns are stationary. A possible explanation for non-stationarity in the whole sample is the presence of the structural break, especially the main break of November 6th 2008. According to Perron (1989), structural breaks tend to effect unit root tests. From these corroborative tests, we can reasonably state that both index levels and returns are stationary.

Table 9. Variance ratio test for random walk

	Whole		Sub-sample 1		Sub-sample 2	
	Log Level	Returns	Log Level	Returns	Log Level	Returns
Joint test	a1.0523	b1.6045	b10.0577***	b3.1547***	b12.7517***	a3.5859***
	(0.749)	(0.369)	(0.000)	(0.006)	(0.000)	(0.001)
Period 2	1.0407	0.4937*	0.5023***	0.4668***	0.4527***	0.5591***
	(0.445)	(0.109)	(0.000)	(0.002)	(0.000)	(0.001)
Period 4	1.0947	0.2612	0.2598***	0.2551***	0.2507***	0.2599***
	(0.293)	(0.120)	(0.000)	(0.004)	(0.000)	(0.000)
Period 8	1.1194	0.1415	0.1200***	0.1354***	0.1135***	0.1282***
	(0.328)	(0.124)	(0.000)	(0.005)	(0.000)	(0.001)
Period 16	1.0657	0.0616	0.0658***	0.0680***	0.0606***	0.0683***
	(0.675)	(0.121)	(0.000)	(0.006)	(0.000)	(0.002)

Note. [a] Max$|z|$ at period 4, [b]Max$|z|$ at period 2.

Numbers in parentheses are p-values.

***, **, *Statistically significant at 1%, 5%, and 10% level, respectively.

Unit root does not necessarily imply random walk, although random walk is a common example of unit root. Therefore, we advance our tests for random walk using the approach proposed in Lo and MacKinlay (1988, 1989) as described in equations (8) to (15). The test results are displayed in Table 9. Additionally, in Figure 7, variance ratio statistics are plotted together with plus or minus two asymptotic standard error bands. The horizontal line at level 1 is a reference for the null hypothesis. The null of random walk is rejected in graphs whose null reference line lies outside the bands (sub-samples). The null hypothesis of random walk is strongly rejected on sub-samples at 1 percent level. However, on the whole sample, the hypothesis cannot be rejected. This might be due to the influence of the main structural shift. Hence, as a caution, we cannot rely on the whole sample to make any valid inference.

Finally, based on the estimated autoregressive process, we test for residual serial correlation and heteroskedasticity using LM and ARCH-LM as described in equations (3) to (7). The results are reported in Table 10. The null hypothesis of no serial correlation is rejected on sub-sample 1 since the test statistics are statistically significant. Note that, the rejection on index levels is strong with 1 percent level of significance, while in returns is only possible on lag order 2 and 4 (at 5 and 10 percent significance level). However, evidence of no serial correlation is strong on the whole and sub-sample 2, although it can be rejected at 1 and 5 percent significance levels. On the other hand, the null of no ARCH in residual is rejected too on sub-sample 1 with a 1 percent statistical significance. The general interpretation is that serial correlation is associated with heteroskedastic in the DSE index, and vice versa. Hence, for sub-sample 1, residuals autocorrelation is associated with a time-variant (non-constant) variance. It is the contrary on the whole and sub-sample 2. This may implies that the main structural shift of November 6th 2008 might have changed the way the market respond to information, in which there was a higher dependence on previous price information prior to the structural shift than after.

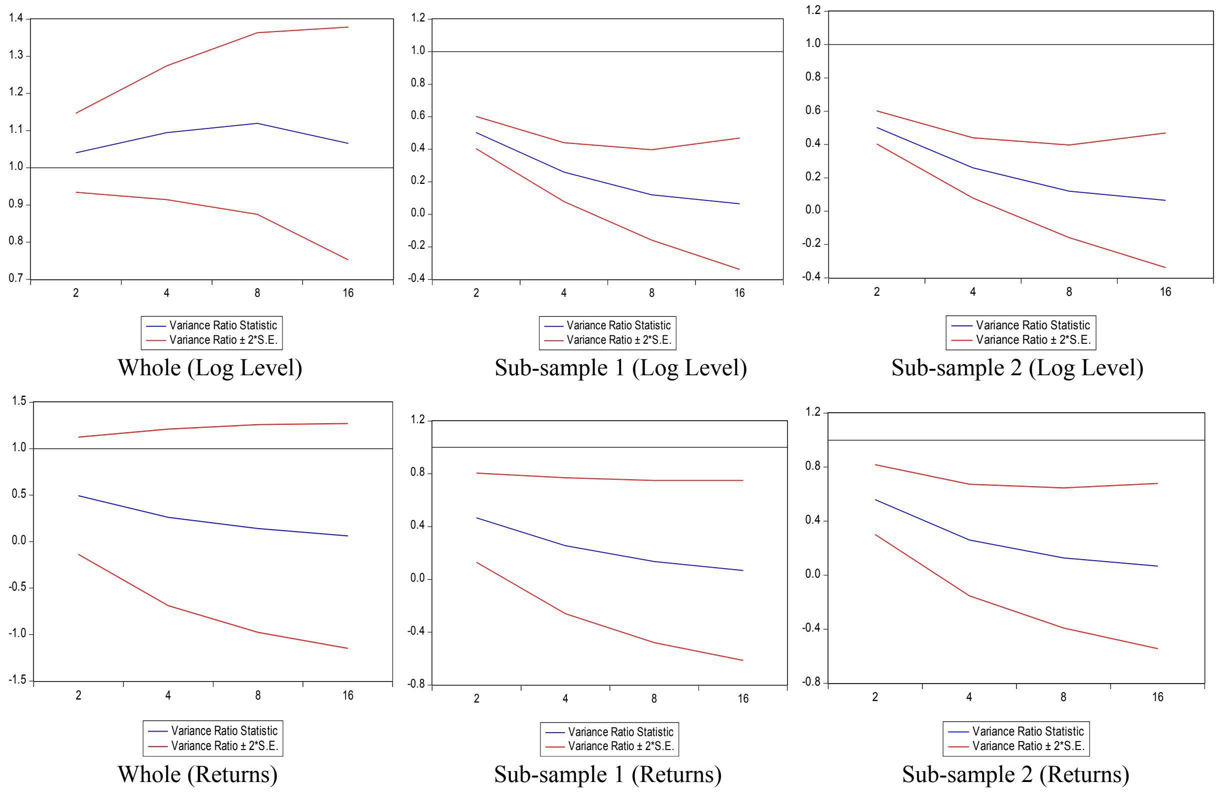


Figure 7. Variance ratio plots for random walk

Table 10. Residual serial correlation and heteroskedasticity

	Lag order	Breusch-Godfrey LM Test		ARCH LM Tests	
		Log Level	Returns	Log Level	Returns
Whole	1	1.6939	3.1410*	0.0235	0.0001
		(0.193)	(0.077)	(0.878)	(0.992)
	2	2.3203*	2.7829*	0.0125	0.0007
		(0.099)	(0.062)	(0.988)	(0.999)
	4	1.8110	1.5906	0.0064	0.0005
		(0.124)	(0.175)	(1.000)	(1.000)
Sub-sample 1	1	14.4757***	0.0578	13.2936***	29.0585***
		(0.000)	(0.810)	(0.000)	(0.000)
	2	7.2950***	3.9441**	6.6210***	14.4785***
		(0.000)	(0.020)	(0.002)	(0.000)
	4	5.4645***	2.0204*	43.7898***	47.8741***
		(0.000)	(0.091)	(0.000)	(0.000)
Sub-sample 2	1	2.7794*	0.9986	0.3944	0.0015
		(0.096)	(0.318)	(0.530)	(0.969)
	2	1.8867	0.6791	0.0497	0.3223
		(0.152)	(0.507)	(0.952)	(0.968)
	4	1.0422	0.3943	0.0060	0.0038
		(0.385)	(0.813)	(1.000)	(1.000)

Note. Numbers in parentheses are F-statistics. ***, **, *Statistically significant at 1%, 5%, and 10% level, respectively.

5. Conclusion

This paper has examines the price discovery mechanism at the DSE using basic econometric methods. These methods are based on fundamental and traditional tests for memory effects. The objective was to use the dynamic features of the DSE stock index and the deterministic features of the market to explain the efficiency of the price discovery mechanism. Specifically, we analyze the distribution of the index in relation to serial correlation, heteroskedasticity and normality as well as measuring for unit root and random walk. Our results, firstly, show strong evidence of non-normality in the index series with high level of leptokurtic distribution in returns. Secondly, both the index levels and returns appear to be stationary. Thirdly, the index appears to exhibit structural shifts, mainly associated with stock listings. Finally, there is evidence that the DSE stock index does not follow a random walk, suggesting inefficient price discovery (Fama, 1970), but not sufficient to conclude that the stock market itself is inefficient or that prices are not rational assessments of fundamental values (Lo & MacKinlay, 1988). Further profound investigations are, therefore, crucial for achieving conclusive inferences.

On one hand, these results can be associated with some characteristic features of the exchange such as inactive trading, illiquidity and high dependence on foreign investors to boost market activities. On the other hand, they relate to the trading and investment behaviors of market participants such as investors' dependence on dividend as the main source of income rather than stock trading, uncompetitive trading among brokers, and motives for more returns from alternative portfolio investments in government securities. We call for policy makers at the DSE and the government to take further measures to improve market efficiency, especially stimulating more competition by amending regulations that limit competitive trading.

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