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Impact of Capitalization on Asset Price Bubble in Dhaka Stock Exchange

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The objective of this paper is to investigate whether any of the financial intermediary factors treated as outliers (which stand here as a proxy of capitalization that results through the public policies and huge liquidity of fungible investment funds in the stock market of Dhaka Stock Exchange (DSE) came through easy bank-loans) play any role for the surge in stock prices which is termed as stock market bubbles. To attain this objective, the study employs two techniques. First, the simulation technique is adopted by incorporating the long memory models of Geweke and Porter-Hudak (1983) and second, the ordinary least square regression technique is used to identify the impacts of capitalization on aggregate stock market price. In the simulation process, observed facts reveal that additive outliers affect the *bias* and *MSE* of the estimated fractional parameter. The size of the additive outliers in the data generating process has also important effects on the estimated fractional parameter. The result exhibits non-trend fluctuations that are influenced by a stochastic process of surge in the stock prices shaping in bubbles in the capital market. It is also shown that huge capital availability in the DSE through easy bank loans and other informal sources has a significant influence on asset prices inflating them often into bubbles.

1. Introduction

Asset price bubble is an economic phenomenon in which values in a particular sector become inflated for a short period. If the bubble bursts, the asset price in that sector collapse (Chapman, 2007; Knight, 2002). Yet, it is hard to predict when this will happen (Black, 2002).

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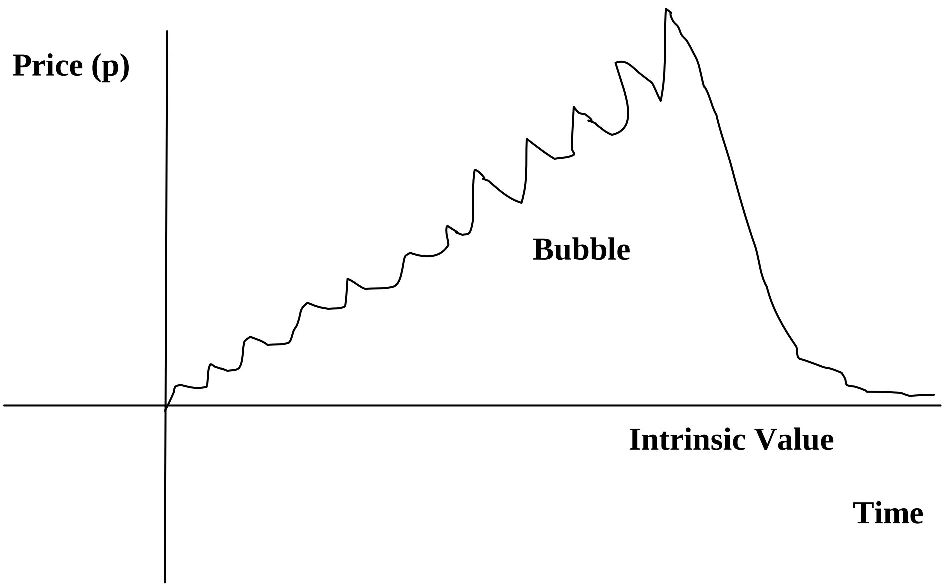
A description of stock market bubble seems to be more useful in Kindleberger (1987) which notes “positive feedback” and “price increases greater than justified by market fundamentals.” A stock market bubble is a type of economic bubble taking place in stock markets when market participants drive stock prices above their value in relation to some system of stock valuation (see Figure 1). In financial markets, a stock market bubble is a self-perpetuating rise or boom in the share prices of stocks of a particular industry. The term may be used with certainty only in retrospect when share prices have since crashed (Kindleberger, 2000). A bubble occurs when speculators note the fast increase in value and decide to buy in anticipation of further rises, rather than because the shares are undervalued. Typically many companies thus become grossly overvalued. When the bubble "bursts", the share prices fall dramatically, and numerous general investors as well as business organizations face serious financial loss and ultimate economic hardship.

Numerous intermediary factors have played a significant role in the formation and collapse of stock market bubbles from early times. One of such examples is the availability of easy credit approval and fungible investment funds that are invested in the stock market for buying company shares (Craven & Islam, 2008). Intermediary effects imply two things - one the one hand, there are interlinks between consecutive or successive bubbles (Allen & Gale, 2002) and also some mediatory dynamics cause to shape the bubbles on the other (Craven & Islam, 2008). Intuitively, these interlinks can be interpreted as an existence of a long memory or long range dependence of intermediate factors and stock market bubbles (Ashraf & Rodriguez, 2006). An example for such interlinks has been cited by Carswell (1960) which shows that there were links between the 1719 bubble in the stock of the Mississippi Company in Paris and the 1720 bubble in the stock of the South Sea Company in London. When these bubbles inflated and burst, there were significant flows of information between these two financial centers. Similarly, there were also flows of information between London and Paris and other financial centers in Europe such as Amsterdam and asset price movements were interdependent (Craven & Islam, 2008). In more recent times, stock market interlinks also appear to play an important role in asset price bubbles. For example, Higgins and Osler (1997) consider 18 OECD countries and document a significant simultaneous rise in real estate and stock prices during the period 1984-89 followed by a subsequent fall in the stock prices during the 1989-1993 period.

Similar observation has also been shared by Rahman (2010) in the case of Dhaka Stock Exchange (DSE) in which the painful memories of 1996 bubble is linked with the recent-scenario of the highly inflated asset prices in early 2010 that is being termed as bubble, because DSE had risen by nearly 125 percent over the period from March 2009 to February 2010. Is the current bull run over or are we in for a bigger bubble and a worst burst? Many times, the asset price bubbles might result in economic downfall (Lewis et al., 2010). There were for example, the burst of bubbles in the tulip crisis of 1637 in Netherlands and the South Sea bubbles incident in 1720 in the UK, the cyclical crises in the 19th century, or the great crisis beginning from 1929. Such a process of burst of speculative bubble may be understood by H. Minsky's post-Keynesian financial instability hypothesis (Itoh, 1990).

Figure 1: A Stock Market Bubble



Yet, how far the role as intermediations such as economic, financial and political can go around is also an important question. In this respect, models of long memory can have some clue to underscore whether there is any interlink between successive share market bubbles and also whether the outlier is a cause to shape a bubble in the stock market having short-term or persistent long term effects.

The prime thrust of this paper is, therefore, to investigate whether any intermediary factor such as capitalization treated as outlier (which stands here as a proxy of capitalization that results through the public policies and huge liquidity of fungible investment funds in the stock market came through easy bank-loans) play any role for large upward variations or surge in stock prices which are termed as stock market bubbles in the case of DSE (Rahman, 2010). To achieve this objective, the study adopts two techniques. First is the simulation technique incorporating the long memory models of Geweke and Porter-Hudak (1983) and the other is the OLS technique which applies the primary data collected from the DSE information archive. The simulation model uses the artificial data generated by Vogelsang (1999) and Perron and Rodriguez (2000) by implementing a Monte Carlo design. If there is any observation that the effects of outliers of exogenous intermediary variables influence the bias, the MSE and the size of t-statistics of the fractional parameter, *d* of the long memory model, it can be concluded that long memory of the past bubbles are present and the intermediary factors have significant impact on affecting trend-stationarity of the asset prices that may lead to inflating the stock prices aberrantly which apparent in the DSE during the period under review.

2. Long Memory Model and Stock Market Bubble

As long memory models have been used by econometricians since around 1980 (Ashraf and Rodriguez, 2009), perhaps the most dramatic empirical success of long memory processes has been in recent work on modeling the volatility of asset prices and speculative revenues. In this context, the approach has yielded much empirical regularities, which have spawned new insights into understanding the stock exchange market behavior and pricing of risk. Very often, stock market prices exhibit bubbles which are disturbed by many economic, financial, psychological and political factors, which are termed as outliers (Craven & Islam, 2008). These outliers are of many kinds by nature. This paper only considers additive outliers which affect the time series process inherent in long memory models (Ashraf, 2001).

Literally, long memory means to rely on past experiences. That is, if something has happened in the stock market in the past, there is a chance to happen again in the future (Ashraf and Rodriguez, 2009). Statistically, in the case of a stationary process with long term autocorrelation function, $\rho(k)$ is said to be a long memory process if $\sum^{\infty}_{k=o} |\rho(k)|$ does not converge (Beran 1994). However, for some models the correlations decay to zero very slowly which implies that the observations far apart are still related to some extent. An intuitive way to describe such behavior is that the process has a long memory (Chatfiled, 1996).

Several models show persistence in shocks and provide an extension of the concept of nonstationarity. An alternative way of testing for nonstationarity models is the process of using the concept of fractional integration. Kennedy (2005) suggests that the concept of fractional integration is useful in testing for nonstationarity in econometric models. The traditional analysis examines $(1-\alpha L)\ y_t = \varepsilon_t$ where $\alpha \geq 1$, whereas the model developed later is $(1-L)^d\ y_t = \varepsilon_t$ where $d \geq 0.5$. In the second case, d takes on non-integer or fractional values, from which follows the term 'fractional'.

Seminally, the idea of long memory models appears to have developed its roots in the physical sciences in the 1950s originated from the work of Hurst (1951). In particular, Hurst (1951) adopts the long memory model to solve the problem of determining the storage capacity required in the Great Lakes of the Nile River Basin to ensure that the reservoir would be able to supply an irrigation system for the agricultural land in Egypt and Sudan with water throughout the year. This most single reference of Hurst (1951) broached the question of the effect of very long term autocorrelation in observed time series analysis which later comes to be known as a long memory process applied in econometric studies (Ashraf and Rodriguez, 2006). This astounding model of a long memory process has, indeed, attracted the attention of econometricians along with the pioneering works in this area of econometrics which include Taqqu (1975), Granger and Joyeux (1980), Granger (1981), Hosking (1981), Geweke and Porter-Hudak (1983), Baillie and King (1996), and Vogelsang, (1999).

A variant of causal forecasting is simulation. The impact on the economy of a variant is simulated by using the econometric model to forecast into the future. With the advent of computer software packages, standard dynamic simulation techniques are reasoned to be immensely popular to study macroeconomic policies (UNO, 2002). The analysis of persistence of some time series has been a topic of research interests, especially in the macroeconomic context. The paradigm of trend stationarity versus difference stationarity involves thinking of persistence as transitory effects versus permanent effects. In the middle of this paradigm exists the analysis of persistence using the fractional integration process, which is known as autoregressive fractionally integrated moving average (*ARFIMA*) process.

There have been several methods to estimate the fractional parameter such as in the time domain and frequency domain based on *OLS* estimation or *Maximum Likelihood Estimation (MLE).* In this paper, *OLS* estimation is used considering frequency domain. As mentioned earlier, the prime objective of this paper is to observe the effect of any external factor such as capitalization in the stock market of DSE treated as additive outlier on the *bias, Means Square Error (MSE)* and size of *t-statistics* of the estimated fractional parameter which subsequently produce stock market bubble and probable stochastic shocks in speculative revenue of the share-holders value yielded in the stock exchange market. The study has employed long memory model developed in frequency domain. The model used the artificial data set generated by Vogelsang (1999) and Perron and Rodriguez (2003) by implementing a *Monte-Carlo* simulation design.

3. Methodology

3.1 Theoretical Framework

There are a variety of ways of estimating the parameter d. In the present study, following Geweke and Porter-Hudak (1983), the definitions of fractional Gaussian noise and integrated or fractionally differenced series are generalized and showed that the two concepts are equivalent. Here, the procedure is based on estimation in the paradigm of frequency domain. For the model $(1 - L)^d x_t = \epsilon_t$, where $\{x_t\}$ is assumed to be a time series process, $d \in (-.5, .5)$ and ϵ_t is serially uncorrelated, the spectral density of the time series $\{x_t\}$ is:

$$f_2(\omega\,; d) = (\sigma^2/2\pi)\ \ |1 - e^{-i\omega}|^{-2d} = (\sigma^2/2\pi)\{4\sin^2(\omega/2)\}^{-d} \qquad (1)$$

A time series with the spectral density $f_2\,(\omega; d)$ is called an integrated or fractionally differenced series, which suggests that $\lim_{\omega\to 0} \omega^{2d} f_2\,(\omega; d) = (\sigma^2/2\pi)$ and the autocorrelation function (for $d \neq 0$) is $\rho_2\,(\tau\,; d) =$

$\Gamma(10d)\ \Gamma(\tau + d) / \Gamma(d)\ \Gamma(\tau + 1 - d)$, which leads to $\lim_{\tau\to\infty} \tau^{1-2d} \rho_2 (\tau; d) = \Gamma (1 - d) / \Gamma(d)$.

Now consider $(1 - L)^d\, y_t = u_t$, where u_t is a linear and stationary distributed process with the spectral function $f_u (\lambda)$, which is supposed to be finite, bounded away from zero and continuous on the interval $\{ -\pi, \pi\}$. Based on this methodology, one has

$$\log \{f_y (\omega_j)\} = \log \{f_u (0)\} - d \log \{4\sin^2 (\omega_j / 2)\} + \log [f_u ((\omega_j) / f_u (0)] \quad (2)$$

and d can be estimated from a regression based on the above equation using spectral ordinates $\omega_1, \omega_2, \ldots, \omega_m$, from the periodogram of y_t, that is $I_y (\omega_j)$:

$$\log \{I_y (\omega_j)\} = a - d \log \{4\sin^2(\omega_j / 2)\} + v_j , \; j = 1\ldots n \quad (3)$$

where

$$v_j = \log [f_u (\omega_j) / f_u (0)] \quad (4)$$

and v_j is supposed to be *i.i.d.* with zero mean and variance $\pi^2/6$. Thus, the least square estimator of d is asymptotically normal. If the number of ordinates n is chosen such that $n = g (T)$, where $g(T)$ is such that $\lim_{T\to\infty} g(T) = \infty$, $\lim_{T\to\infty} \{ g (T) / T\} = 0$ and $\lim_{T\to\infty} \{(log(T)^2 / g(T) = 0$ then the *OLS* estimator of d in (3) takes the limiting distribution as follows:

$$(est\ d - d) / \{var\ (d)\}^{1/2} \sim N\ (0, 1) \quad (5)$$

When the *OLS* estimator d is significantly different from zero, the sample of the specific size is fractionally integrated. Here, in this estimation, $n = g (T) = \sqrt{T}$.

3.2 Simulation Design

A Monte Carlo simulation tool is used in this study which consists of generating repeated samples of artificial data for some sample size and analyzing the behavior of the relevant statistics (Kennedy, 2005). In this case, the attention is focused on the behavior of the estimates of the fractional parameter. One way to do this is to calculate some characteristics of this estimate such as the MSE and the bias (e.g. Ashraf, 2001). As the size and power of the t-statistics is one of the principal focuses of the present analysis, the study calculates the number of rejections of the null hypothesis in all the replications used.

The same data generating process is followed as that of considered in Vogelsang (1999) and Perron and Rodriguez (2000) involving the case where additive outliers are considered. The process could be defined as follows:

$$y_t = n_t + \sum_{i=1}^{m} \delta_i D((T_{a0,\ i})_t + u_t \qquad (6)$$

$$(1 - L)^d u_t = \mathrm{v}_t \qquad (7)$$

where, $v_t \sim i.i.d.N(0,1), d$ is the fractional parameter, $D((T_{a0,\ i})_t = 1$ if $\mathrm{t} = \mathrm{T}_{a0,\ i}$ and 0 otherwise and δ_i is the size of the additive outliers. Four sizes of additive outliers are considered (that is m = 4 in expression (6)), along with two different assumptions about their values. In the first case, $\delta_i = 0$ ($for\ i = 1,2,3,4$). This case illustrates that no outliers, no size distortions and no bias are observed in the estimates. In the second case, $\delta_1 = 10, \delta_2 = 5, \delta_3 = 2, \delta_4 = 2$. This is indicative that the effects of additive outliers of "large" size are present. The second specification is close to that used by Perron and Rodriguez (2000). The goal is to see the effects of large additive outliers. The variable n_t represents the deterministic component. In the experiment, it considers only the case where a constant is included in the regressions; that is, $n_t = \mu$. In the simulations of the expression (6), it, without loss of generality, includes the case where, $\mu = 0$. The sample sizes considered in the study are $T = 50, 100, 200, and\ 500$. These sample sizes are fairly common as in any empirical work. The number of replications considered for each set of parameters is 1000 and a seed of 12345 is used. The number of simulations used is similar to those of used in the literature of Pedro (2001).

The study includes the effect of aberrant observations using three indicators such as the *bias*, MSE and exact size of *t-statistic* of the estimated fractional parameter, *d*. The bias is defined as the difference between the true parameter value and expected value of the estimate. In formal expression: *bias* = *E* [*d*^ - *d*], where *E* denotes the expectation operator. The *MSE* is calculated as: *MSE* (*d*^) = $bais^2$ – $var(d\^{})^2$, where *var* denotes variance.

3.3 Regression Model

In parallel to the laboratory test of simulation, this study aims to investigate the field level impacts of the surge of capitalization (which is treated as outlier in the simulation model) on the aggregate stock market prices in DSE. To this aim, the study formulates the following single variable linear regression model which incorporates the observed data collected from the DSE information archive. Thus, the model is:

$$Y_t = \alpha + \beta X_t + \varepsilon_t$$

where,

Y_t: Aggregate stock market price index (in Bangladesh currency of Taka on daily basis)

X_t: Capital value (in Bangladesh currency of Taka on daily basis)

α, β : Parameters to be estimated

ε_t: The disturbance term

The DSE general index is used as the aggregate stock market price index and the capital value is taken as the total market capitalization in DSE which are collected from the DSE Archive (2010).

4. Results and Discussions

4.1 Simulation Results

First, the results are considered for the case where outliers are generated in a simple additive manner. Tables 1- 4 present the results for the case where there are no additive outliers. In terms of the *bias* and *MSE*, there are no significant variations for all of the fractional parameter values ascribed. The *MSE* is observed to be different for the two extreme values of *d*. In fact, when *d* is close to unity, the *MSE* is smaller. This is so, because the bias and the variances are smaller, which happens probably as a consequence of a better estimation of the fractional parameter in opposition to the case where *d* is close to –1. This result implies that in absence of outliers uncertainties in the stock market are in small magnitude, which indicates that in the absence of massive capitalization in the stock market the asset price variations are not much significant as well.

Table 1: Bias, MSE and t-statistic with no additive outliers and sample size 50

Parameter D	Bias	MSE	Size of t-statistic H_0: $d = 0$	Size of t-statistic H_0: $d = 1$
-0.96	0.18	0.20	0.61	0.96
-0.72	0.09	0.17	0.46	0.95
-0.48	0.05	0.16	0.30	0.92
-0.24	0.03	0.16	0.16	0.85
0.00	0.02	0.16	0.10	0.75
0.24	0.02	0.16	0.20	0.56
0.48	0.03	0.16	0.38	0.35
0.72	0.05	0.15	0.60	0.17
0.96	0.02	0.13	0.82	0.11

Table 2: Bias, MSE and t-statistic with no additive outliers and sample size 100

Parameter D	Bias	MSE	Size of t-statistic H_0: $d = 0$	Size of t-statistic H_0: $d = 1$
-0.96	0.21	0.14	0.74	1.00
-0.72	0.09	0.10	0.62	1.00
-0.48	0.02	0.09	0.40	0.99
-0.24	0.01	0.09	0.20	0.97
0.00	0.01	0.09	0.08	0.90
0.24	0.01	0.09	0.19	0.73
0.48	0.02	0.09	0.46	0.46
0.72	0.03	0.09	0.76	0.20
0.96	0.02	0.07	0.92	0.09

Table 3: Bias, MSE and t-statistic with no additive outliers and sample size 200

Parameter *D*	Bias	MSE	Size of t-statistic H_0: $d = 0$	Size of t-statistic H_0: $d = 1$
-0.96	0.20	0.13	0.86	1.00
-0.72	0.07	0.06	0.80	1.00
-0.48	0.02	0.05	0.56	1.00
-0.24	0.00	0.05	0.22	1.00
0.00	0.00	0.05	0.06	0.98
0.24	0.00	0.05	0.27	0.90
0.48	0.01	0.05	0.62	0.64
0.72	0.03	0.06	0.89	0.24
0.96	0.01	0.05	0.97	0.07

Table 4: Bias, MSE and t-statistic with no additive outliers and sample size 500

Parameter *D*	Bias	MSE	Size of t-statistic H_0: $d = 0$	Size of t-statistic H_0: $d = 1$
-0.96	0.24	0.12	1.00	1.00
-0.72	0.09	0.04	1.00	1.00
-0.48	0.03	0.03	1.00	1.00
-0.24	0.01	0.03	1.00	1.00
0.00	0.01	0.03	0.05	1.00
0.24	0.01	0.16	1.00	1.00
0.48	0.02	0.03	1.00	1.00
0.72	0.04	0.03	1.00	1.00
0.96	0.01	0.03	1.00	0.09

When the true parameter $d = 0$, the exact size is closer to the nominal size when sample size increases and that result is actually expected. When the true fractional coefficient is closer to –1, the null hypothesis is strongly rejected that the fractional coefficient is equal to zero. That means if there are no outliers present in the design, it has no impact on the estimation of the parameter *d*. It implies that in the absence of abnormal observations of the massive capital value in the stock market, there is no such probability of forming any stock market bubbles as well as their crashes. On the other hand, when the true fractional coefficient is close to unity, it is difficult to reject the null hypothesis that the coefficient is different from one. This is also true for very larger sample sizes such as T = 100, T = 200 and T = 500. This result is consistent with the general expectation and the case of unit root tests.

Tables 5 - 8 present the results for the case when there are some large and small additive outliers. For the sample sizes T= 50, 100, and 200, the exact size for the null hypothesis that d = 0 is closest to zero when the true fractional parameter is closer to –1. The reverse is true when the true fractional parameter is closer to unity. The opposite case arises when the true exact size of the null hypothesis that the fractional parameter is equal to unity. However, no size distortion is observed when we use T = 500, a sample size that is, unfortunately, not frequently available in macroeconomic applications.

The results with respect to the bias and *MSE* are also related to the behavior of the true fractional parameter. In fact, when this parameter is closer to –1, bias and *MSE* appear to increase. The reverse is true when d > 0 but less than unity. For this sample size, the bias is important when d < 0. Although bias and *MSE* are smaller for T = 500, the exact size of the t-statistic of the null hypothesis that d = 1 is higher compared to other sample sizes.

Table 5: Bias, MSE and t-statistic with large /small additive outliers and sample size 50

Parameter *D*	Bias	MSE	Size of t-statistic H_0: d = 0	Size of t-statistic H_0: d = 1
-0.96	0.86	0.76	0.03	0.95
-0.72	0.61	0.41	0.04	0.95
-0.48	0.37	0.18	0.04	0.93
-0.24	0.13	0.08	0.06	0.92
0.00	-0.09	0.11	0.07	0.86
0.24	-0.23	0.18	0.08	0.77
0.48	-0.27	0.19	0.13	0.58
0.72	-0.24	0.19	0.35	0.34
0.96	-0.19	0.16	0.63	0.15

Table 6: Bias, MSE and t-statistic with large /small additive outliers and sample size 100

Parameter D	Bias	MSE	Size of t-statistic H_0: d = 0	Size of t-statistic H_0: d =1
-0.96	0.82	0.68	0.05	0.99
-0.72	0.57	0.34	0.06	0.99
-0.48	0.32	0.13	0.07	0.98
-0.24	0.07	0.05	0.10	0.98
0.00	-0.11	0.08	0.09	0.96
0.24	-0.18	0.11	0.08	0.88
0.48	-0.17	0.11	0.26	0.68
0.72	-0.12	0.11	0.63	0.33
0.96	-0.08	0.08	0.87	0.12

Under the given condition of the case of *d* is close to unity, this behavior is similar to the power problems observed for most of unit root tests in the econometric literature. Finally, some issues that pertain to all sample sizes need to be mentioned here. First, when Table 2 is compared with Table 1, it observes the direct effects of additive outliers are present against a case where no aberrant observations exist. The evidence with respect to higher bias and higher *MSE* is also obvious. Moreover, it can be readily observed that there are size distortions for the t-statistic of the null hypothesis that d = 0. Thus, it is obvious from this evidence that there are significant impacts of capitalization in the DSE on the surging of the stock prices which ultimately causes to make a bubble.

Table 7: Bias, MSE and t-statistic with large /small additive outliers and sample size 200

Parameter D	Bias	MSE	Size of t-statistic H_0: d = 0	Size of t-statistic H_0: d = 1
-0.96	0.93	0.88	0.01	1.00
-0.72	0.67	0.46	0.02	1.00
-0.48	0.40	0.18	0.03	0.99
-0.24	0.14	0.06	0.07	0.99
0.00	-0.01	0.05	0.07	0.98
0.24	-0.05	0.06	0.19	0.92
0.48	-0.03	0.06	0.56	0.69
0.72	0.00	0.06	0.87	0.28
0.96	0.00	0.05	0.97	0.07

Table 8: Bias, MSE and t-statistic with large /small additive outliers and sample size 500

Parameter *D*	Bias	MSE	Size of t-statistic H_0: d = 0	Size of t-statistic H_0: d =1
-0.96	0.91	0.84	1.00	1.00
-0.72	0.65	0.43	1.00	1.00
-0.48	0.36	0.14	1.00	1.00
-0.24	0.09	0.03	0.96	1.00
0.00	-0.01	0.03	0.05	1.00
0.24	-0.01	0.03	0.98	1.00
0.48	0.01	0.03	1.00	1.00
0.72	0.03	0.03	1.00	1.00
0.96	0.01	0.03	1.00	0.63

As mentioned, one of the motives of this paper is to analyze the effects of additive outlier of massive financial capitalization present in the asset market on the behavior of the estimated value of the fractional parameter. With this end in view, an extensive set of simulation has been done employing additive outliers. When there are additive outliers which are generated according to the pre-specified data generating process, the exact size of the t-statistic of the null hypothesis that d = 0 goes to zero. This fact is more pertinent particularly when the true fractional parameter is negative. The opposite situation occurs or the t-statistic of the null hypothesis that d = 1 when the true fractional parameter is positive. In the case of the bias and the *MSE*, t-statistics are more affected by the size of the fractional parameter. Comparison between a situation in which there exists additive outliers (observations on aberrant behavior of massive influx of financial capitalization present in the stock market) to a situation in which these kinds of observations do not exist, showed that they have important effects on the estimation of the fractional parameter and on the estimation of the t-statistic for verifying the null hypothesis that d = 1 or d = 0. Overall, it is has been observed that clear size distortions and the bias and the *MSE* are higher or clearly different with respect to the case where these kinds of observations do not exist. This outcome implies that intermediary factors such as capital influx present in the stock market are effectively changing the asset price trend and this trend is not following any systematic variation rather inducing an abnormal random walk phenomenon that is effectively responsible for forming bubbles. This study lends further support to

Allen and Gale (2002), and Craven and Islam (2008) that different financial, political and psychological intermediaries may cause to form the stock market bubbles.

4.2 Primary Evidence in DSE

In analyzing the impact of capitalization on the aggregate general price of the stock market, the study employs the regression technique. The regression results are based on the sample size of 1456 daily data starting from January 1, 2004 to June 24, 2010. The model incorporates single exogenous variable of market capitalization of DSE in order to see its sole explanatory impact on asset price bubble. The analysis has been done with the SPSS 13.0 version. Though in analyzing time series data, there is a need to ensure the unit root property of the series, the study purposively excludes it. As the primary motive of this section of analysis is to see the direct impact of capitalization on the asset prices rather than to see its stationarity or non-stationarity property, the study uses only the regression analysis. The regression results indicate that explanatory variable of market capitalization and the intercept are statistically positively significant at .001 levels which are provided in the Table 9.

Table 9: Impact of capitalization on stock market prices of DSE

	Coefficients	**Standard Error**	**t-Statistics**
Intercept	1192.466	10.955	108.854***
Capital Value	1778E-03	000	155.855***
Adjusted R^2	0.94		
F	24290.88***		
N	1456		

Note: ***p<.001, **p<.01, Dependent variable = Stock market price

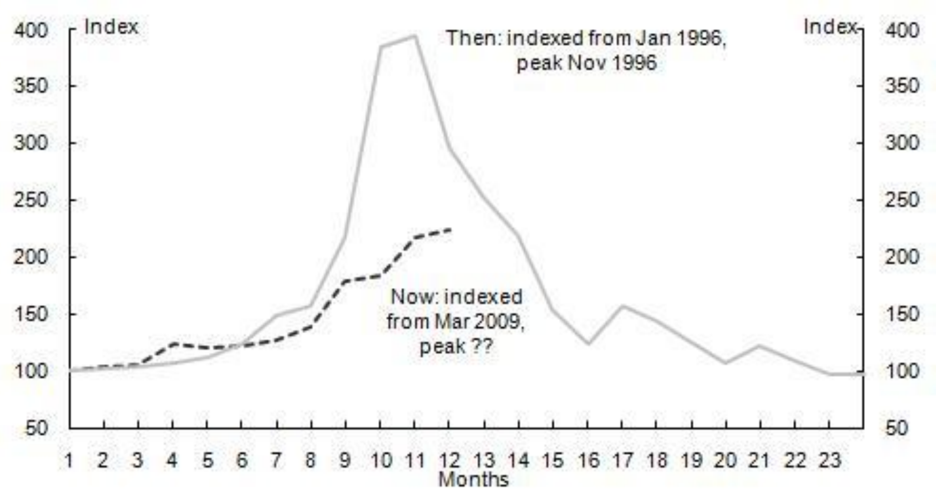
The adjusted R^2 value is 0.94 which indicates that financial capital can alone explain the variability in asset prices by 94 percent and only 6 percent variability is due to other factors which are not incorporated in the regression model of this study. Now the question remains how this result of the regression estimation can be interpreted as a result of financial intermediations which take place in DSE in Bangladesh. This interpretation will assist to realize how it initiates a bubble as well as the indirect role of the banking system in extending loans which may cause a bubble to burst.

Standard theories of asset pricing presume that people buy assets and stocks with their own capital. In most financial systems, this is not whole true (Allen and Gale, 2000). Many of the investors used to buy houses, stocks and other assets with other people's money. The purchase of real asset is normally debt-financed. If the investment is finally successful, the borrower repays the loan and retains the difference between the value of the asset and the principal plus interest. If the investment failed, the borrower has limited liability and the lender bears the loss (Allen and Gale, 2000). In a similar fashion, a significant proportion of stocks are held by mutual-pension funds and insurance companies. Finance managers also have incentives to be a risk-lover. If the investment plan is successful, the managers can expect to be rewarded by a split of the returns, but most notably it will attract new investors to invest in the future. As the firms collect management fees in proportion to the assets under control, the managers will be significantly better off as a result of their good performance. If the investment policy fails, there is a limit to the downside risk that the manager bears. In the worst case, these failed managers lose the jobs but in any way the liability is limited. Hence, when financial intermediaries formulate investment decisions, the incentive scheme they face exhibits convex payoffs. This is termed as agency problem in the finance literature (Allen and Gale, 2000).

If there is an agency problem as portrayed above, the people articulating the investment plans will have a reason to go for risky ventures. As a matter of fact, lenders are not in a position to observe all the features present in a project which implies that the borrowers can shift risk to the lending agents and amplify their payoffs. This reality encourages investors to bid up the prices of risky assets above the fundamental values and consequently it causes a bubble. The more risky the asset, the greater is the amount that can be shifted and the larger is the bubble will be (Allen and Gale, 2000). This risk can emerge from two sources, namely the asset revenue risk and the financial risk. The financial risk is the risk associated with future financial conditions such as the amount of credit that will be available through the intermediary role of the banking systems.

The bulls in the DSE are running ahead with all share price index of the DSE crossing 6,324-mark recently. The surge in the price index and the associated increased market volatility somehow remind the boom and bust of 1996 in the DSE (see Figure 2).

Figure 2: Comparing recent price rises in DSE with what happened in 1996



Note: Adopted from Mansur and Hoque (2010).

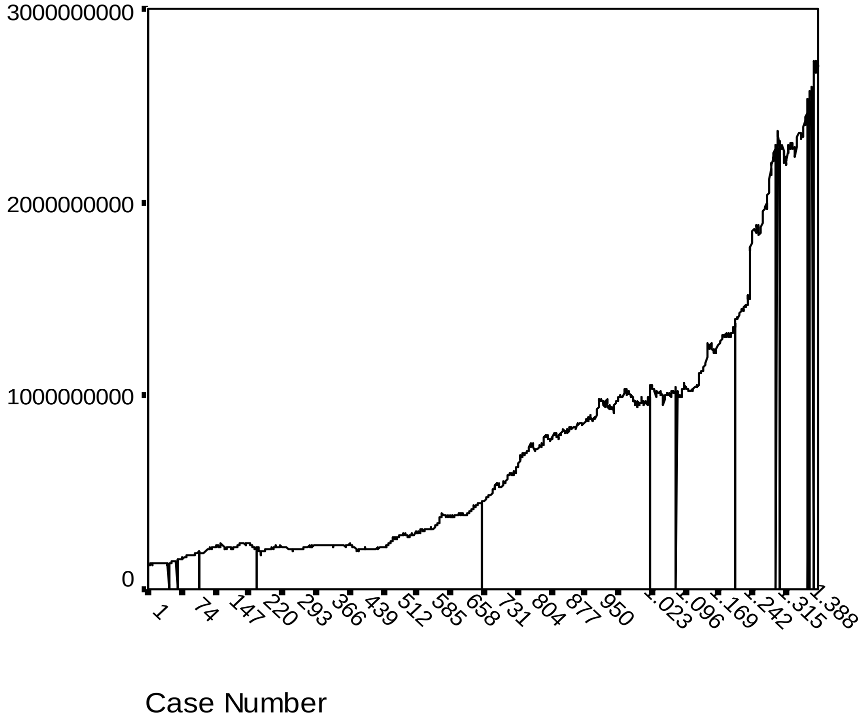
A sudden influx of funds and a surge in retail investors are pushing the DSE index forward without regard to economic fundamentals, but the unfolding scenario is virtually a re-enactment of the early period of the 1996 stock market episode. Obviously when there is a lot of liquidity and fungible money in the system, there is no way to prevent people from borrowing that is officially stated for the purpose of trading, housing, agriculture and other uses and investing in the stock market (Mansur and Hoque, 2010).

Irrespective of the on-going debate on whether the bubble is on the verge of burst or not, it is being observed that there is a bubble in the DSE (Rahman, 2010). This bubble may be resulted through microeconomic as well as macroeconomic phenomena (Uddin, 2009). Among the macroeconomic phenomenon, fiscal, monetary and financial factors are involved (Allen and Gale, 2000). Generally, most stock market bubble episodes have some common characteristics. Some of these characteristics include exuberant demand manifested through weak correlation between price and economic value, high price volatility, acceleration in money and margin lending, narrow market leadership, structural weaknesses like lack of institutional investors and weak regulatory regime (Mansur and Hoque, 2010). In the current economic environment of Bangladesh, there has been involved a plethora of stimulators that are blamed to cause directly or indirectly to induce the asset price bubble in DSE.

Assessing the existence and size of exuberant demand is a difficult task. However, as new records for the DSE general index week after week are observed, we really wonder whether "irrational exuberance" is also dominating the DSE. The index, which was at 2,941 in August 2009, has crossed 5800 points in February 2010 (see Figure 2), or a growth of 98 percent. This surge is certainly not normal and cannot be explained by economic fundamentals (Rahman, 2010; Mansur and Hoque, 2010).

Similar dynamics have been recorded in market capitalization, price-earnings ratio, market volatility and in other indicators during this period. Market capitalization (total number of shares times the average market price of shares) in August 2009 was Tk 1,307 billion (US$18.9 billion) and on February 17, 2010 it has risen to Tk 2366 billion (US$ 34.2 billion), recording an increase of 81 percent within the five-month period. Just to put it in proper perspective, the market capitalization was only Tk 97 billion (US$ 1.7 billion) in Dec 2003 before the beginning of the current bull-run. The daily average turnover showed a similar trend, increasing from Tk 0.14 billion in Dec 2003 to Tk 12 billion in January 2010 and further to Tk 14 billion in the first half of February. In 2009, daily turnover did not fall below Tk 10 billion which was a miniscule Tk 0.26 billion in 2004 (Mansur and Hoque, 2010). In Figure 3, the surge in market capitalization in DSE is shown which incorporates data on daily basis from January 1, 2004 to June 24, 2010 representing the peak on the vertical axis at present.

Figure 3: Trend in Market Capitalization in DSE from January 1, 2004 to June 24, 2010



While the supply of stocks is almost unaffected, except for the launching of Grameen Phone IPO in November 2009, pressures in stock prices are simply exerted from the demand side. Among many factors, huge number of new investors with fresh funds is primarily responsible for this price pressure. In January 2009, some 0.115 million new Beneficiary Owners' (BOs) accounts have been opened while, the number was 58,000 in December 2009. The increase in the number of BO account holders has accelerated further to 0.123 million in the first 10 days of February. This means that 12,000 new investors are joining the market every day (Mansur and Hoque, 2010). Huge amounts of fresh money are being channeled into the stock market through these accounts, undoubtedly pumping the stock market balloon to grow bigger almost every day. If the average account size is Tk 0.1 million, everyday Tk 1.2 billion is being poured into the market, mostly by the first time retail investors (Rahman, 2010).

Now the question remains why this is happening and what else the government can do in order to prevent a repeat of 1996 stock market debacle. Obviously when there is an enormous liquidity in the system and money being fungible, there is no way to stop people from borrowing and investing in the stock market. As surging flood water cannot be contained by putting a weak dam downstream and water simply bypasses or overwhelms or washes away the barrier, money keeps pouring into the stock market ignoring the Security and Exchange Commission’s (SEC) signals lured by quick capital gains (Uddin, 2009).

With broad money (M2) expanding by more than 20 percent last fiscal year and once again this year, fueled by inflow of workers' remittances, certainly there is more than enough liquidity to shrug off the limited efforts by the SEC. The budgetary provision to allow whitening of black money into the stock market is also playing an important role in flooding the market with liquidity (Rahman, 2010).

Presently, it is being observed that people of all walks of life are moving toward the stock market for investment, but the market is not for everyone. Professionals and market manipulators are expected to gain, while others must lose at the end. The market is already overheated and in the midst of the stock market frenzy, market manipulators are very active. All these uncomfortable indicators send one clear message that the stock market is currently not a good time for new and uninformed investors. It is imperative on the part of policy makers to send clear warning signals and highlight the heightened risks in order to protect ordinary investors. Measures are also needed to be taken to minimize the exposure of banks to the stock market in order to safeguard depositors' interest (Mansur and Hoque, 2010).

5. Conclusion

The main objective of this paper is to analyze the impact of financial capitalization on the asset prices which would form bubble eventually. First, the paper attempts to observe the long memory evidence of asset price bubble and then employs the ordinary least square regression method in order to see the impact of the liquidity of financial capital in DSE in Bangladesh. In the case of simulation, the impact of additive outliers is observed on the estimated value of the fractional difference parameter, *d.* Overall, additive outliers or aberrant size of market capitalization are observed to affect the bias and the *MSE* and the size of t-statistics. This result implies that there has been a momentary shock process involved rather than a systematic trend in the asset price change. This outcome appears to be grim and could results in no more than a complex process of momentous stochastic uncertainty in forming the stock market bubble which is not at all desirable in order for maintaining a healthy share market trade.

The regression results show that surge in market capitalization has a highly statistical significant impact on the stock market aggregate price index. The abnormal observation on market capital accumulation in DSE is particularly remarkable since 2009. Myriads of potential reasons are thought to be active in shaping the asset price bubble in DSE based on the evidence noted earlier in the text. However, the enormously surging market capitalization in DSE creating asset price bubbles owing to the potential reasons that are stylized in this paper can be summarized as: (a) credit policies for lending existed in the banking and financial systems are based on very easy terms and conditions by which new investors from all walks of life are funneling fungible funds to the capital market enormously; (b) significant amount of foreign remittance is being invested into stock market; (c) budgetary provision of opportunity to transform huge black money into white money mostly of which is spent for purchasing stock share and (d) expansionary fiscal policy which has a spillover effect into increasing money and capital availability in the stock market.

The analyses provided in the text indicate a potential rationale for policy makers to monitor the stock market. Since asset prices in the stock market serve as a signal to investors to invest, bubbles can mislead the investors when it is not profitable. The overinvestment, which becomes apparent after the bubble bursts, can lead to a period of low investment and that can cause a recession. Thus, policy makers ought to step in to end the bubble before asset prices go too far out of line relative to their fundamentals.

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