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Evidence of long range dependence in Asian equity markets: the role of liquidity and market restrictions

Daniel O. Cajueiro[a,*], Benjamin M. Tabak[b]

[a] Universidade Católica de Brasília, Mestrado em Economia de Empresas, SGAN 916, Módulo B, Asa Norte DF 70790-160, Brazil
[b] Banco Central do Brasil, SBS Quadra 3, Bloco B, 9 Andar DF 70074-900, Brazil

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Abstract

In this paper, the efficient market hypothesis is tested for China, Hong Kong and Singapore by means of the long memory dependence approach. We find evidence suggesting that Hong Kong is the most efficient market followed by Chinese A type shares and Singapore and finally by Chinese B type shares, which suggests that liquidity and capital restrictions may play a role in explaining results of market efficiency tests.

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1. Introduction

The literature on market efficiency is vast as the theme is of interest for both practitioner and academics. Since it is a very intriguing issue, a big part of this literature focuses on seeking long memory dependence in asset returns. Actually, if the stock returns present long range dependence, the random walk hypothesis is not valid anymore and neither does the market efficiency hypothesis [1]. Moreover, the presence of long range dependence in asset returns contradicts the weak form of market efficiency

* Corresponding author.
E-mail address: danoc@pos.ucb.br (D.O. Cajueiro).

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which states that, under the information contained on the set formed by past returns, future returns are unpredictable [2].

This paper tests long-range dependence for three different countries: China, Hong Kong and Singapore. While the Chinese equity market is an emergent market which has two types of shares—one that is restricted to local investors (Class A shares) and other that is available only for foreign investors (Class B shares)—Hong Kong and Singapore are two developed economies. Thus, we have here a unique opportunity to test the effect of these differences of these two types of Chinese shares on the formation of the long-range dependence phenomena.

In this paper, our measure of long-range dependence is the Hurst's exponent. Additionally, since market efficiency (predictability) seems to evolve over time [3], we measure this exponent statically (as the usual approach) and also dynamically.

The rest of the paper is divided as follows. Our measure of long-range dependence considered here are introduced in Section 2. In Section 3, the data used in this work is presented. In Section 4, the methodology employed in this paper is presented. In Section 5, the empirical results of this work are exposed. Finally, Section 6 presents some conclusions of this work.

2. Measures of long-range dependence

In this paper, the Hurst's exponent calculated by the classical R/S analysis [4,5] is our measure of long range dependence.

The R/S analysis [4,5] due to its simplicity is the most popular way to detect long-range dependence. Let $X(t)$ be the price of a stock on a time t and $r(t)$ be the logarithmic return denoted by $r(t) = \ln(X(t+1)/X(t))$.

The R/S statistic is the range of partial sums of deviations of times series from its mean, rescaled by its standard deviation. So, consider a sample of continuously compounded asset returns $\{r(1), r(2), \ldots, r(\tau)\}$ and let $\bar{r}_\tau$ denote the sample mean $1/\tau \sum_\tau r(\tau)$ where τ is the time span considered. Then the R/S statistic is given by

$$(R/S)_\tau \equiv \frac{1}{s_\tau}\left[\max_{1\leqslant t\leqslant\tau}\sum_{t=1}^{\tau}(r(t)-\bar{r}_\tau) - \min_{1\leqslant t\leqslant\tau}\sum_{t=1}^{\tau}(r(t)-\bar{r}_\tau)\right] , \tag{1}$$

where s_τ is the usual standard deviation estimator

$$s_\tau \equiv \left[\frac{1}{\tau}\sum_t (r(t)-\bar{r}_\tau)^2\right]^{1/2} . \tag{2}$$

Hurst [4] found that the rescaled range, R/S, for many records in time is very well described by the following empirical relation:

$$(R/S)_\tau = (\tau/2)^H . \tag{3}$$

Table 1
Market information

	Number of listed companies (US$ millions)	Average company size	Market capitalization (US$ millions)	Market turnover %
China	853	271.2	343,394	130.1
Hong Kong	658	521.9	231,322	54.4
Singapore	321	294.3	94,469	50.5

3. Data

This study comprises three different markets: the Chinese stock market, the Hong Kong stock Market and the Singapore stock market.

In the Chinese market two classes of stocks are traded: the so-called Class A shares which are only available to Chinese nationals and the so-called Class B shares which are only available to foreign investors. [1] Thus this market represents a unique opportunity to study the effects of information transmission, since there are major differences in the market for these two types of shares. [2] On the other hand, Hong Kong and Singapore are two developed economies. [3]

Our main hypothesis is that there must be differences on market efficiency for these two types of shares. If we assume that institutional investors may have superior information (asymmetric information), then their trading could either increase or reduce (weak form) efficiency in the market. Furthermore, if liquidity plays a role in explaining (weak form) efficiency, then Class B shares should be less efficient than A shares.

We utilize daily returns from October, 1992 through December, 2000 for both Class A and B shares (we analyze both the Shanghai and the Shenzhen stock exchanges, which are weighted-averages, and market capitalization indices). Additionally, we also study the Hang Seng index for Hong Kong and the straits time index for Singapore (market capitalization-weighted indices). All the data used in this paper was taken from the Bloomberg database. In Table 1 we present some market information for these equity markets. Hong Kong and Singapore have some similarities but the market capitalization and average company size of Hong Kong are much higher for the former. The Chinese equity market, on the other hand, has an average company size similar to that of Singapore but the market capitalization is more than three times higher.

[1] In February, 2001 these markets have been released for Chinese investors and thus our data sample ends in December, 2000.

[2] The average volume traded in Class A shares is approximately 40 times the average volume of trades in stocks in Class B, therefore Class A shares should be more liquid. Furthermore, the main investors in Class A shares are individuals while Class B shares are mainly owned by large foreign institutional investors.

[3] It is interesting to stress that there is no overlapping between stocks that comprise these indices used in this study. For China the companies traded in both indices are the same but each index has a different type of share (A and B).

4. Methodology

In this paper, we use two different approaches to evaluate the Hurst's exponent: (1) the usual approach where the Hurst's exponent is calculated in a static way for the entire series; (2) a "rolling sample" approach considered in [3].

While (1) is the usual approach to calculate the measures of long range dependence, (2) can be better explained by the following example. Consider we have 2040 daily observations for the Hang Seng Index. We use the first 1008 observations (4 years of data) and calculate the Hurst exponent for this time series, then we drop the first observation and use the next day, also using 1008 observations, and calculate the Hurst exponent. We proceed with this sampling approach until the last observation is used and we plot these time varying Hurst exponents. In the case in hand we would have 1032 Hurst exponents. This methodology serves the purpose of identifying whether long range dependence seems to change over time, which agrees with the idea that market efficiency changes over time [3].

Therefore, two different results will be presented for each time-series: (a) The Hurst's exponent H calculated by means of the statical approach. In this case, if $H = 0.5$, then there is no evidence of long-range dependence. On the other hand, if $H > 0.5$, then there is evidence of long-range dependence with persistent behavior and if $H < 0.5$, then there is evidence of long-range dependence with anti-persistent behavior. Biggest $|H|$ implies in strongest evidence of long range dependence. (b) The Hurst's exponent calculated by means of the "rolling sample" approach. Since this approach makes available several Hurst's exponents for each country and it is impossible to compare all of them, then we make statistical inference with the means, medians and other statistical measures of these Hurst exponents in order to compare their market inefficiency degree.

5. Results

In Table 2 we present autocorrelations up to six lags for the indices in this study with their respective Q statistics and p-values underneath. The first that is worth noting is that first order autocorrelations are very high for Singapore, Shanghai and Shenzhen B, while there are much lower for the other indices. Nonetheless, all these indices seem to exhibit autocorrelation in log returns. [4]

[4] Due to the presence of these autocorrelations and also to the Lo's critique [6] of the R/S analysis that this statistics is sensitive to the presence of short range dependence, we also apply to this data a modified version of R/S analysis considered in [7]. In this modified version of the R/S analysis, we apply the R/S analysis to shuffled data in blocks of size 5 (and 10), i.e., we pick a random permutation of the data series within each block of size 5 (10) and apply the R/S analysis to this shuffled data. The effect of random permutations in these small blocks is to destroy any particular structure of autocorrelation within these blocks. In this work, we avoid the Lo's modified R/S statistics since this method has a strong preference for accepting the null hypothesis of no long range dependence independently of whether long range dependence is presented in the data or not (for details, see Refs. [8,9]). However, since the results of these additional tests (performed by using the R/S statistics applied to shuffled data) are similar to the results presented here (quantitatively and qualitatively), we do not show these results in the paper.

Table 2
Autocorrelations for time series returns

Lags	Hong Kong	Singapore	Shanghai A	Shanghai B	Shenzhen A	Shenzhen B
1	0.04	0.18	0.02	0.19	0.01	0.15
	2.87	65.02	0.44	76.55	0.34	44.12
	0.09	0.00	0.51	0.00	0.56	0.00
2	−0.02	0.02	0.03	0.00	0.06	0.07
	4.02	65.93	2.48	76.57	6.35	54.98
	0.13	0.00	0.29	0.00	0.04	0.00
3	0.09	−0.04	0.09	0.04	0.01	0.07
	19.01	69.14	17.94	79.81	6.40	63.52
	0.00	0.00	0.00	0.00	0.09	0.00
4	−0.06	0.01	0.04	0.03	0.06	0.05
	26.47	69.34	21.47	81.36	12.79	68.41
	0.00	0.00	0.00	0.00	0.01	0.00
5	−0.03	−0.04	0.05	−0.01	0.03	0.03
	28.59	72.99	26.38	81.74	14.23	70.35
	0.00	0.00	0.00	0.00	0.01	0.00
6	−0.01	−0.04	−0.05	−0.01	−0.06	−0.01
	28.88	76.21	30.93	81.89	21.02	70.55
	0.00	0.00	0.00	0.00	0.00	0.00

The first line presents the autocorrelation coefficient and the second and third lines the Q-statistic and it's p-value, respectively.

Table 3
The Hurst's exponents

Hong Kong	Singapore	Shanghai A	Shanghai B	Shenzhen A	Shenzhen B
0.573 ± 0.009	0.609 ± 0.007	0.548 ± 0.009	0.587 ± 0.010	0.564 ± 0.007	0.638 ± 0.011

In Table 3, we present the Hurst's exponent [5] calculated by means of the statical procedure. [6]

In Figs. 1–6, we present results for a "rolling sample" approach for Hurst exponents calculations over the period from October, 1992 to October, 1996. [7] As we can see

[5] The estimation interval in Table 3 is actually a 95% confidence interval.

[6] To give support to our results, these Hurst's exponents were also calculated by the Detrended fluctuation analysis (DFA) [10,11]. The results are qualitatively the same as the ones presented in Tables 3 and 5. They are presented in which follows: $H_{\text{Hong Kong}} = 0.550 \pm 0.007$, $H_{\text{Singapore}} = 0.582 \pm 0.006$, $H_{\text{Shanghai A}} = 0.551 \pm 0.008$, $H_{\text{Shanghai B}} = 0.626 \pm 0.005$, $H_{\text{Shenzhen A}} = 0.566 \pm 0.006$, $H_{\text{Shenzhen B}} = 0.666 \pm 0.004$.

[7] Since we are using four year time windows to calculate the Hurst's exponents and our Hurst's exponents span over the period from October, 1992 to October, 1996, one may notice that the data used to calculate these Hurst's exponents span over the period from October, 1992 to December, 2000.

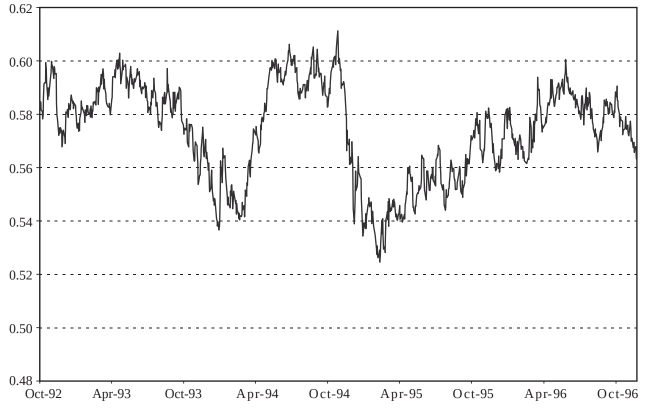

Fig. 1. Plot of the "rolling sample" approach for Hurst exponents calculations for the Hong Kong stock market index.

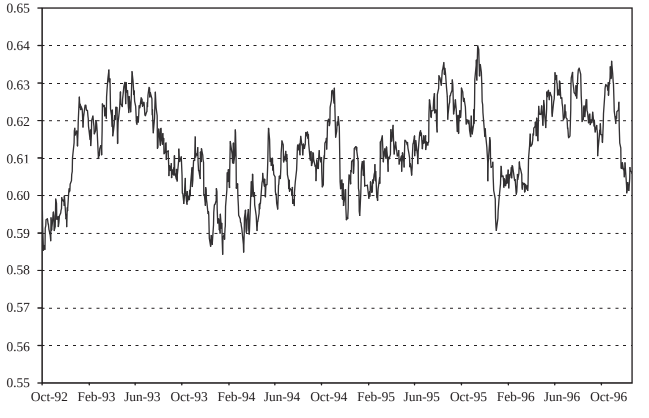

Fig. 2. Plot of the "rolling sample" approach for Hurst exponents calculations for the Singapore stock market index.

these Hurst exponents are well above 0.5 and for most time series seem to be time varying. In Table 4 we present descriptive statistics for these Hurst exponents for each one of the six indices. As we can see, the distribution of these Hurst exponents is not normal and therefore we should compare the medians of the Hurst exponents to compare these indices.

In Table 5 we rank the indices for the countries that we are studying and find that the most inefficient indices are the B shares for China, and Singapore, which have the low market capitalization indexes. Nonetheless, these medians are very high if compared to the benchmark 0.5 as well as the results found in other studies (see, for instance Ref. [12] who find evidence suggesting that Singapore presents long-range dependence, indicating that this market is inefficient), suggesting that these markets possess long range dependence.

Fig. 3. Plot of the "rolling sample" approach for Hurst exponents calculations for the Shanghai A stock market index.

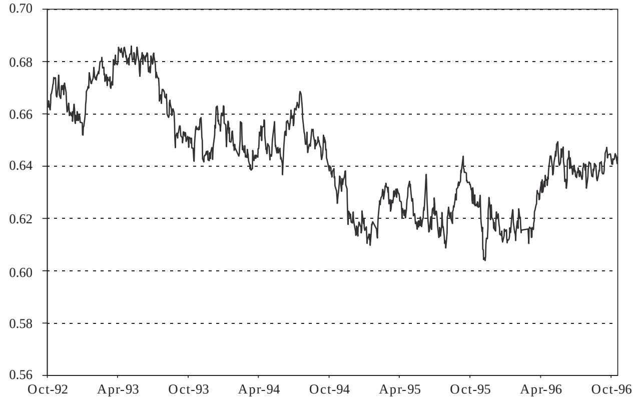

Fig. 4. Plot of the "rolling sample" approach for Hurst exponents calculations for the Shanghai B stock market index.

Table 4
Descriptive statistics for rolling Hurst exponents

	Singapore	Hong Kong	Shenzhen A	Shenzhen B	Shanghai A	Shanghai B
Mean	0.61	0.57	0.60	0.67	0.58	0.64
Median	0.61	0.58	0.60	0.66	0.59	0.64
Maximum	0.64	0.61	0.64	0.79	0.64	0.69
Minimum	0.58	0.53	0.56	0.59	0.53	0.60
Jarque-Bera	27.19	58.67	6.99	88.76	19.83	41.39
p-value	0.00	0.00	0.03	0.00	0.00	0.00

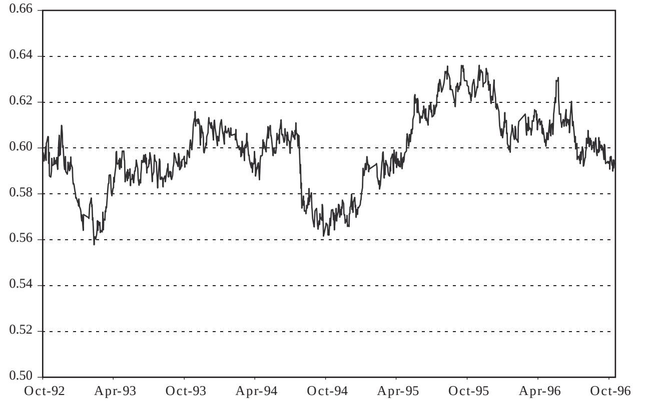

Fig. 5. Plot of the "rolling sample" approach for Hurst exponents calculations for the Shenzhen A stock market index.

Fig. 6. Plot of the "rolling sample" approach for Hurst exponents calculations for the Shenzhen B stock market index.

Table 5
Ranking using median Hurst exponents

Hong Kong	0.58
Shanghai A	0.59
Shenzhen A	0.60
Singapore	0.61
Shanghai B	0.64
Shenzhen B	0.66

In order to compare these medians we employ a nonparametric statistic and results are presented in Table 6. From these tests we can see that these medians are statistically different, and therefore our ranking is meaningful.

Table 6
Nonparametric tests for equality of medians

Method	df	Value	Probability
Med. Chi-square	5	3754.616	0
Adj. Med. Chi-square	5	3745.785	0
Kruskal-Wallis	5	4418.652	0
Kruskal-Wallis (tie-adj.)	5	4419.06	0
van der Waerden	5	4095.435	0

6. Conclusions

In this paper, we investigate the long-range dependence phenomena in three Asian markets, namely Hong Kong, Singapore and China, and find evidence that these markets present long range-dependence. We also build a ranking from lowest to highest inefficiency and find that liquidity and market capitalization may play a role in understanding results coming out from tests for long range dependence. These results suggest that more research is needed on testing for long range dependence for different markets and on increasing our understanding of the possible causes and origins of long range dependencies. Theoretical models that address these issues should be particularly welcome.

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