Testing Long Memory in Stock Returns of Emerging Markets: Some Further Evidence

Hiremath, Gourishankar S and Bandi, Kamaiah

Gokhale Institute of Politics and Economics, Pune, University of Hyderabad, Hyderabad

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Gourishankar S. Hiremath
Gokhale Institute of Politics and Economics
Pune – 411004. India
Email: gsdastapur@gmail.com

Bandi Kamaiah
Department of Economics
University of Hyderabad
Hyderabad – 400054. India

The paper examines the long memory in stock returns of emerging markets. Unlike earlier studies, present study carries out a biased reduced semi-parametric test to detect long memory in mean process and uses diverse and updated data set. The test results finds no strong evidence of long memory in mean process of stock returns both in emerging and developed markets. This is in contract with earlier studies, which conclude that emerging markets in general characterized by long memory process. Hence, long memory is not a peculiar characteristic of emerging markets but appear to be stylized fact of asset returns irrespective of stage of development of the market. Short memory models are thus sufficient to forecast the future returns.

Testing Long Memory in Stock Returns of Emerging Markets:
Some Further Evidences

1. Introduction

Long memory or long range dependence is an important aspect of stock market returns, which departs from random walk hypothesis has gained much attention during the past one and half decade. Long memory is a characteristic of a stationary process in which the underlying time series realizations display significant temporal dependence at very distant observations. The persistent temporal dependence between distant observations indicates possibilities of predictability and hence provides opportunity for speculators to forecast future returns based on past information and make extra normal returns. The presence of long memory in stock returns invalidates the efficient market hypothesis (EMH) according to which, current prices reflect all the available and relevant information and therefore it is not possible to predict their future movements based on past information (Fama 1970). The asset-pricing model would also be invalid in the presence of long-memory. Besides, linear modelling would result into misleading inference in the presence of long memory. Perfect arbitrage is not possible when returns exhibit long-range dependence (Mandelbrot 1971). The early evidence of random walk behaviour of stock returns would be invalid in the presence of long memory.

In this backdrop, the present paper examines the presence of long memory in mean process in stock returns of the emerging markets. The rapid growth of emerging markets since the recent past, and increasing importance of these markets in global finance have attracted the attention of global investors. Consequently, there has been increasing interest among market players, researchers and policy makers to understand these markets. The

issue of long memory though has important theoretical implications and practical relevance, has not received much attention in the emerging markets. It is a common proposition that stock returns in the emerging markets follow long memory due to low liquidity, less developed financial instruments, weak regulatory framework etc.

The focus of the paper is appropriate and it departs from previous studies on this subject in many important ways. First, the sample used in the study is large, richer and more diverse than that of most previous studies. The previous studies on long memory in emerging markets focused on individual markets, while the present paper carries out a cross-country analysis. Compared to other cross-country studies, this study has the advantage that it uses a more diverse group of markets. The sample characteristics make the results of the present study robust and reduce the risk of overemphasizing the generality of the findings. Furthermore, the study departs from the earlier study by carrying out a method proposed by Andrews and Guggenberger's (2003) to test the presence of long memory in mean process of stock returns. The test is an improvement over the semi-parametric tests largely employed in previous empirical analyses. This is the first study, to best of our knowledge, which carried out the test to examine the issue. The remainder of the paper organized as follows: Section - 2 gives a brief introduction of the theory of long memory and notes major empirical evidences. Section 3 briefly describes testing methods. Section 4 discusses empirical results and the last section provides the concluding remarks.

2. Long Memory Definitions.

There are various definitions of long memory. According to McLeod & Hipel (1978), a covariance stationary time series, R_t is said to exhibit long memory if

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$$\sum_{k=-\infty}^{\infty} |\psi(k)| = \infty \qquad \qquad \dots (1)$$

where $\psi(k)$ is the autocorrelation at lag k. This infinite sum condition suggests that correlation at a very distant lags cannot be ignored. Long memory generally defined in terms of time domain and frequency domain. In time domain, a stationary discrete series R_t said to exhibit long memory if its autocovariances decay hyperbolically. In symbols

$$\psi(k) \sim k^{2d-1} \zeta_1(k), \qquad k \to \infty \qquad \qquad \dots (2)$$

where k is time lag, $\psi(k)$ is as defined in (1), d is the long memory parameter, and $\zeta_1(.)$ is a slowly varying function. In frequency domain, a stationary stochastic discrete time series R_t defined by its spectral density function. This represented as in the following equation:

$$f(\omega) \sim |\omega|^{2d} \zeta_2(1/|\omega|), \qquad \omega \to \infty \qquad \qquad \dots (3)$$

for ω is the frequency in a neighbourhood of zero and $\zeta_1(.)$ is a slowly varying function[1].

The long memory models have been in existence in physical sciences such as, geo-physics. Hurst's (1951) developed a rescaled range statistics (R/S) to study long-range dependence in river flows. Mandelbrot (1972) has applied R/S test, which compares the range of partial sums of deviation from the sample mean, rescaled by sample standard deviation, to stock returns. Later, Mandelbrot and Van Ness (1968) developed stochastic model, which explains dependence over a long period. Granger & Joyeux (1980) and Hosking (1981) introduced fractional differencing in autoregressive integrated moving average (ARIMA) framework. They developed a fractional differencing model, which allows a fractional value in integration order of the ARIMA model. Hence, the model known as autoregressive fractionally integrated moving average (ARFIMA). 'The

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[1].An alternative definition of long memory based on Wold decomposition is not discussed here to save space. For a detailed discussion, see Palma (2007)

fractionally differenced process can be regarded as a halfway house between I (0) and I (1) paradigms' (Baillie, 1996).

A time series $\{y_t\}$ follows ARFIMA (p, d, q) process if

$$\phi_p(B)\, y_t = \theta_q(B)\,(1 - B)^{-d}\,\varepsilon_t \qquad \qquad \ldots (4)$$

where $\phi_p (B) = 1+\phi_1 B \ldots + \phi_p B^p$, and $\theta_q(B) = 1+ \theta_1 B+\ldots + \theta_q B^q$ are respectively autoregressive and moving average polynomials of orders p and q, and B is back shift operator. It is assumed that the ϕ (B) and θ (B) have no common roots, and (1-B) $^{-d}$ is fractionally differencing operator defined by binomial expansion.

$$(1 - B)^{-d} = \sum_{j=0}^{\infty} n_j B^j = n\,(B) \qquad \qquad \ldots (5)$$

In equation (5)

$$n_j = \frac{\Gamma(j + d)}{\Gamma(j + 1)\Gamma(d)}$$

$$\ldots (6)$$

In equation (6), Γ denotes the gamma function. For d < ½ d≠0, -1, -2 . . . and $\{\varepsilon_t\}$ is a white noise sequence with finite variance.

The parameter d determines the memory process. If d>0, the autocorrelation functions slowly decay hyperbolically and process exhibit long memory, whereas if d=0, the process has short memory or weak dependence. When d < 0, the process called as anti-persistent and displays negative memory. If d > -0.5, the ARFIMA process is invertible and has linear Wold representation and if d < 0.5, it is covariance stationary. Therefore, if 0<d<0.5, the process said to be stationary and exhibit long memory. The fractional parameter can be estimated from the data. In empirical work, various methods have been used to estimate fractional parameter.

Greene and Fielitz (1977) conducted the first systematic empirical study of long memory. They have employed Hurst's (1951) R/S statistic on 200 individual stocks of NYSE and found that the US stock returns contain long memory. Lo (1991) modified the test and demonstrated that in the presence of short run dependence in the form of heteroscedasticity, R/S test suggested by Mandelbrot (1972) is significantly a biased estimator. He proposes a modified R/S test, which is robust to non-normality and heteroscedasticity. Lo's (1991) modified R/S test subsequently became one of the popular tests employed in the empirical research to detect long-range dependence. A semi-parametric test proposed by Geweke and Porter-Hudak (1983) is the most important test of long memory extensively carried out in the empirical research. However, Andrews and Guggenberger (2003), Agiakloglou *et al* (1993) and Nielsen & Frederiksen (2005) have shown that test severally biased particularly in finite samples. Hence, the inferences drawn from such results are not relevant.

A large number of studies have focused on well-developed markets and evidences are mixed [See, Cheung and Lai 1995; Sadique and Sivapulle, 2001; Lobato and Savin, 1998, among others]. However, it is interesting to see whether stock returns of emerging equity markets, exhibit long memory properties. A limited number of studies which focused on emerging markets though provided mixed evidence but largely concluded that long memory exist in mean and volatility of stock returns in the emerging markets than their counter parts, the developed markets [See, Chaudhury, 2001; Crato and Lima, 1994; Kasman and Torun, 2007; Floros *et al*, 2007, Mc. Millan and Thupagale, 2011][2]. The peculiar characteristics of the emerging markets such as regulatory framework, lack of transparency, differences in institutions, and thinness of the markets cited in the literature

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[2] Most of these studies focused on long memory in variance.

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as important factors inducing long memory. This provides the necessary background and motivation for the present study to re-examine the issue of long memory in equity markets of emerging economies.

3. Data and Testing Methods

The study uses the data of daily stock returns of twenty stock indices for the period March 1990 to March 2010. The major index of the following countries are selected: The U.S, the U.K, France, Germany, Australia, Japan, Australia, Hong Kong, Singapore, Malaysia, China, Indonesia, Brazil, Mexico, South Africa, South Korea, Taiwan, India, Russia, Columbia, and Chile. The data coverage, however, is different for different indices as dictated by availability of the data (see table 1). Data set of twenty indices both from developed and emerging markets has another advantage as it helps to measure relative efficiency of markets represented by different indices and sensitiveness of results to the degree of development of the market. Bloomberg is source of the data.

To estimate fractional integration in mean returns, a bias-reduced log periodogram test proposed by Andrews & Guggenberger (2003, ABBR henceforth) employed in the study. To compare the results, the Geweke & Porter-Hudak (1983, GPH henceforth) semi-parametric test also carried out. Fractionally integrated GARCH of Baillie *et al* (1996), known as FIGARCH estimated to capture long memory persistence in variance. GPH test is simple in application and robust to non-normality. Geweke & Porter-Hudak (1983) proposes a semi-parametric approach to estimate fractional integration value, *d*. The spectral regression to estimate *d* can be expressed as

$$\log I(\lambda_j) = \log f_0(0) - d \log\left[2 \sin\frac{\lambda_j}{2}\right] + \varepsilon_t \quad J = 1, 2\ldots, m \qquad \ldots (7)$$

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where $I(\lambda_j)$ is the periodogram at harmonic frequency, $(\lambda_j) = \frac{2\pi_j}{T}$ (j = 0, ..., T − 1), T is the total number of observations and $m = T^\mu for \ 0 < \mu < 1$ is the number of harmonic ordinates used in the spectral regression. The $I(\lambda_j)$ computed as the product of 2/T and square of the exact finite Fourier transform of the series at the respective harmonic ordinate. The bandwidth m must be chosen such that for T → ∞, m → ∞, m/T → 0. The estimates are sensitive to the number of special ordinates from periodogram of returns (m). The GPH in the present study performed choosing values m=T$^{5.0}$ T,$^{5.5}$ and T $^{6.0}$

The GPH suffers from asymptotic bias and hence Andrews & Guggenberger (2003) proposes a bias reduced log periodogram estimator to reduce the asymptotic order of the bias. The method is the same as that of GPH estimator except that it replaces the constant in "Eq (7)" by the polynomial $\sum_{r=0}^{R} \zeta_r \lambda_j^r$. The estimator $\hat{d}_r$ (of the long memory) is the least squares estimator of the coefficient on -2log λ_i in a regression of log of the periodogram. The AGBR adds regressors $\lambda_j^2 \lambda_j^3 ... \lambda_j^{2r}$ to the regression model. The test uses polynomial in place of constant to model the logarithm of the spectral density of the short run dynamics in the vicinity of origin and thus reduces the bias. Andrews and Guggeneberger (2003) suggest that bias-reduced log-periodogram estimator performs well for the small values of r such as r=1 and r=2. When r=0 the test becomes GPH. The simulation results of Nielsen and Frederiksen (2005) have demonstrated that test not only outperforms semi-parametric tests but also the correctly specified time domain parametric methods.

4. Empirical Analysis

The present section discusses the empirical results. The basic statistics for the index returns are given in table 2. Brazil and China register highest average returns. This reflects

the performance of these markets owing to considerable growth of economy and flood of investors to these economies particularly in the past decade. The mean returns for all indexes are low but positive with the exception of Japan and Taiwan, where mean returns are negative. The table 2 further shows that Brazil has the highest standard deviation, followed by Russia and China. The volatility on an average is relatively high in the emerging markets compared to the developed markets (see table 2). The significant negative skewess implies that the returns are flatter to the left compared to normal distribution. Further, significant Jarque-Bera test statistics indicate that returns are non-normal

To detect the long memory in mean returns, the GPH test performed on the daily stock returns of 20 markets and the results are reported in table 3. The number of special ordinates from periodogram of returns (m) to include in the estimation of d must be chosen judiciously as otherwise they produce inaccurate estimation of d. The value of d is estimated choosing m = $T,^{5.0}$ $T,^{5.5}$ and $T,^{6.0}$. It is evident from the table that index returns of Malaysia, Indonesia, Brazil, South Korea, Russia, Columbia and Chile are generated by long memory process as the value of d is within theoretical value i.e $0<d<0.5$. The estimated fractional parameter is insignificant for China, South Africa, Taiwan and India. Singapore is the only market among developed countries, which shows long –range dependence in mean process. The results seem to confirm that stock returns in emerging markets possess long-range dependence. The significant d values for these indices range between 0.14 (Russia) to 0.19 (Chile).

Since the GPH suffers from asymptotic bias, we carry out the AGBR test, which substantially mitigates the first and higher order biases of GPH. The value of d estimated

with r=1 and r=2 (r is additional regressors) and the results are furnished in table 4. It can be observed from the table that the test statistics are quite different from GPH test statistics. The estimated fractional value d is significant only for Brazil and Chile in the panel of emerging markets. The GPH results for these two markets are similar however. GPH test found Malaysia, Indonesia, Mexico, South Korea, Russia, Columbia following long memory in mean process but AGBR test has not found any significant presence of long memory in these markets. Both the test carried out here show that China, South Africa, Taiwan, and India have not exhibited long memory. Among developed markets, the AGBR test results reveal that the US stock returns exhibit presence of long memory and fractional parameter values are insignificant for rest of the developed markets. The substantial evidence of long memory in stock returns of emerging markets of GPH may be due to first and higher order bias as pointed out by different scholars. Therefore, the results of AGBR test are reliable and hence preferable to other tests of long memory.

The study found that out of the 12 emerging markets, only Brazil and Chile exhibited long memory in the mean process. The U.S is the only exception among the developed markets, which has shown tendency of long memory in mean returns. The evidence of long memory indicates possibility of predictable components in data series of Brazil, Chile and the USA and hence invalidates the EMH in these markets. The weak evidences of long memory found in the present study are in contrast with the view that long memory exist in the emerging markets than the developed counterparts. The earlier evidences, which support such view, may be because of application test such as GPH, which suffers from asymptotic bias. The results suggest that long memory is a stylized feature of asset returns and independent of stage of development of the market.

6. Concluding Remarks

The present study has examined the issue of long memory in the emerging markets. To detect long memory in mean returns, AGBR test was carried out. The test is an improvement over other semi-parametric tests. The data set is quite comprehensive and covers the period of reforms, market microstructure changes in emerging markets. The GPH test results show that most of emerging markets exhibit long memory in mean returns. However, AGBR test found long memory only in returns of Brazil and Chile. The results of the study do not support the proposition held generally by previous studies that emerging markets largely characterized by long memory than developed markets. Hence, presence of long memory in volatility is stylized fact of asset returns and independent of stage of development of market. AGBR results are quite reliable and preferable to other tests long memory. The absence of long memory implies that short memory models are sufficient to forecast future returns.

References

Agiakloglou, C., Newbold P and Wohar, M (1993), "Bias in Estimator of the Fractional Difference Parameter" *Journal of Time Series Analysis*, Vol. 14, pp. 235-246.

Andrews, DWK and Guggenberger P (2003), "A bias-reduced log-periodogram regression estimator for the long-memory parameter", *Econometrica*, Vol. 71, pp. 675-712.

Baillie, R. T (1996), "Long memory and fractional integration in econometrics", *Journal of Econometrics*, Vol. 73, pp. 5-59.

Baillie, R. T, Bollerslev, T and Mikkelsen H. O (1996), 'Fractionally integrated generalized autoregressive conditional heteroskedasticity', *Journal of Econometrics* vol. 74, pp. 3-30.

Cheung, Y. W and Lai, K. S (1995), "A search for long memory in international stock market returns", *Journal of International Money and Finance*, Vol. 14, pp. 597-615.

Choudhry, T (2001), "The long memory of time-varying beta: examination of three emerging Asian stock markets", *Managerial Finance*, Vol. 27, pp. 5-23.

Fama, E. F (1970), "Efficient capital markets: A review of theory and empirical work", *Journal of Finance*, Vol. 25, pp.383-417

Floros, C, Jaffry Y and Lima, G. V (2007), "Long memory in Portuguese stock market", *Studies in Economics and Finance*, Vol. 24, pp. 220-232

Geweke, J and Porter-Hudak, S (1983), "The estimation and application of long memory time series models", *Journal of Time Series Analysis*, Vol. 4, pp. 221-238.

Granger, C.W.J and Joyeux, R (1980), "An introduction to long-memory time series models and fractional differencing", *Journal of Time Series Analysis*, Vol. 1, pp. 15-29.

Greene, M. T and Fielitz, B (1977), "Long-term dependence in common stock returns", *Journal of Financial Economics*, Vol.4, pp.339-349.

Hosking, J. R. M (1981), 'Fractional differencing'. *Biometrika,* Vol. 68, pp. 165-176.

Hurst H. E 1951, "Long-term storage capacity of reservoirs', *Transactions of the American Society of Civil Engineers'*, Vol. 116, pp. 770-799.

Kasman, A. and Torun, E (2007), "Long Memory in the Turkish stock market return and volatility", *Central Bank Review,* Vol. 2, pp. 13-27.

Lo, A. W (1991), Long term memory in stock market prices, *Econometrica*, Vol. 59, pp.1270-1313.

Lobato, I and Savin N. E (1998), "Real and spurious long-memory properties of stock-market data", *Journal of Business and Economic Statistics*, Vol. 16, pp. 261-268.

Mandelbrot, B (1971), "When can price be arbitraged efficiently? A limit to the validity of the random walk and martingale models", *Review of Economics and Statistics*, Vol. 53 pp. 225-236.

Mandelbrot, B. B and Van Ness J. W (1968), "Fractional brownian motions, fractional brownian noise and applications", *SIAM Review*, Vol. 10, pp.422-437.

Mandelbrot, B. B (1972), 'Statistical methodology for non periodic cycles: From the covariance to R/S analysis', *Annals of Economic and Social Measurement*, Vol.1, pp. 259-290.

McLeod, A. I & Hipel, K. W (1978), "Preservation of the rescaled adjusted range 1: A re assessment of Hurst phenomenon" *Water Resources Research*, Vol. 14, pp. 491-508.

McMillan, D., and Thupayagale, P, "Measuring volatility persistence and long memory in the presence of structural breaks: Evidence from African stock markets", *Managerial Finance*, Vol. 37, pp. 220 - 232

Crato, N., and Lima, J.F (1994), "Long-memory and Nonlinearity: A Time Series Analysis of Stock Returns and Volatilities", *Managerial Finance,* Vol, 20, pp. 219 - 241

Nielsen, M. O and Frederiksen, P. H (2005), "Finite sample comparison of parametric semiparametric and Wavelet estimates of fractional integration", *Econometrics Review*, vol. 24, pp. 405-443.

Palma, W, 2007, '*Long-memory time series*', New Jersey: John Wiley & Sons, Inc.

Robison, P.M, (1991), "Testing for strong serial correlation and dynamic conditional heteroskedasticity in multiple regression", *Journal of Econometrics*, Vol. 47, pp. 67-84.

Sadique, S and Silvapulle, P (2001), "Long-term memory in stock market returns: International evidence", *International Journal of Finance and Economics*, Vol. 6, 59-67.

Table 1: Data Sample

S.No	Markets	Time Period
1	US	01/03/1990 to 03/12/2010
2	UK	01/03/1990 to 03/12/2010
3	France	01/03/1990 to 03/12/2010
4	Germany	01/03/1990 to 03/12/2010
5	Japan	01/05/1990 to 03/12/2010
6	Australia	01/03/1990 to 03/12/2010
7	Hong Kong	01/03/1990 to 03/12/2010

8	Singapore	09/01/1999 to 03/12/2010
9	Malaysia	01/31/1992 to 03/12/2010
10	China	12/20/1990 to 03/12/2010
11	Indonesia	01/04/1990 to 03/12/2010
12	Brazil	01/03/1990 to 03/12/2010
13	Mexico	01/20/1994 to 03/12/2010
14	South Africa	07/03/1995 to 03/12/2010
15	South Korea	01/04/1990 to 03/12/2010
16	Taiwan	01/04/1990 to 03/12/2010
17	India	07/05/1990 to 03/12/2010
18	Russia	09/04/1995 to 03/12/2010
19	Columbia	07/04/2001 to 03/12/2010
20	Chile	01/03/1990 to 03/12/2010

Table 2: Basic Statistics

Markets	Mean	Std.Dev	Skewness	Kurtosis	Jarque-Bera (P value)
Developed Markets					
US	0.0002	0.0117	-0.202	9.147	0.0000
UK	0.0001	0.0114	-0.119	6.555	0.0000
France	0.0001	0.0141	-0.042	4.725	0.0000
Germany	0.0002	0.0147	-0.099	4.792	0.0000
Japan	-0.0002	0.0157	-0.018	5.233	0.0000
Australia	0.0002	0.0092	-0.554	7.085	0.0000
Hong Kong	0.0004	0.0172	0.0008	9.047	0.0000
Singapore	0.0001	0.0013	-0.233	7.090	0.0000
Emerging Markets					
Malaysia	0.0000	0.0165	0.393	45.526	0.0000

China	0.0007	0.0260	5.339	135.54	0.0000
Indonesia	0.0003	0.0158	-0.004	8.902	0.0000
Brazil	0.0032	0.0325	0.056	19.385	0.0000
Mexico	0.0001	0.0168	-0.007	5.932	0.0000
South Africa	0.0004	0.0132	-0.497	6.099	0.0000
South Korea	0.0001	0.0179	-0.184	3.865	0.0000
Taiwan	-0.0000	0.0179	-0.231	2.493	0.0000
India	0.0006	0.0183	-0.117	6.033	0.0000
Russia	0.0007	0.0286	-0.369	6.673	0.0000
Columbia	0.001	0.0148	-0.227	12.249	0.0000
Chile	0.0007	0.0120	0.238	5.845	0.0000

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Note: Basic statistics for stock returns of 20 markets given in the table. The null of skewness and kurtosis =0, is significantly rejected. The last column provides probability value for Jarque-Bera test.

Table 3: Estimates of Fractional Differencing Semi parameter *'d'* (GPH)

	m=0.50	*m*=0.55	*m*=0.60
Developed Markets			
US	0.072	0.034	0.045
	(0.93)	(0.53)	(0.91)
UK	-0.012	-0.008	0.001
	(-0.14)	(-0.13)	(0.01)
France	-0.011	-0.027	-0.004
	(-0.11)	(-0.40)	(-0.07)
Germany	0.060	0.048	0.027
	(0.77)	(0.78)	(0.56)
Japan	-0.014	0.023	-0.018
	(-0.16)	(0.34)	(-0.35)
Australia	0.042	0.023	0.073
	(0.54)	(0.38)	(1.46)
Hong Kong	-0.012	0.021	0.065
	(-0.15)	(0.36)	(1.34)
Singapore	0.173	0.192	0.140
	(2.15)**	(2.42)**	(2.18)**
Emerging Markets			

Malaysia	0.090	0.161	0.065
	(0.94)	(2.16)**	(1.16)
China	0.014	0.121	0.082
	(0.21)	(1.57)	(1.46)
Indonesia	-0.061	0.113	0.168
	(-0.76)	(1.70)	(3.28)*
Brazil	0.320	0.176	0.145
	(3.22)	(2.42)	(2.60)**
Mexico	0.008	-0.062	-0.020
	(0.09)	(0.82)	(0.36)
South Africa	0.003	0.072	0.046
	(0.16)	(0.98)	(0.86)
South Korea	0.117	0.065	0.111
	(1.35)	(1.01)	(2.09)**
Taiwan	0.018	0.017	0.032
	(0.20)	(0.26)	(0.63)
India	-0.096	0.009	0.043
	(-1.31)	(0.17)	(0.91)
Russia	0.164	0.173	0.141
	(1.92)*	(2.40)**	(2.56)**
Columbia	0.141	0.193	0.193
	(2.11)**	(2.07)**	(2.57)**
Chile	0.091	0.158	0.137
	(2.12)**	(2.13)**	(2.28)**

Note: Value in each cell of the table represents fractional integration, *d,* estimated by GPH semi parametric method. The values of 'd' obtained by choosing m=T 5.0, T5.5 and T 6.0, T. *m is* special ordinates from periodogram of returns. The t statistics are given in parenthesis. The null of unit root is tested against long memory alternative. *, ** indicates significance at 1 % and 5 % level.

Table 4: Andrews and Guggenberger (2003) Biased Reduced Test Statistics

	r=1	r=2
Developed Markets		
US	0.299	0.339
	(2.20)*	(2.11)*
UK	0.029	0.286
	(0.21)	(1.58)
France	0.144	0.200
	(1.06)	(1.10)
Germany	0.112	0.172
	(0.82)	(0.95)
Japan	0.069	-0.006
	(0.50)	(-0.03)
Australia	0.099	0.018
	(0.27)	(0.10)
Hong Kong	0.017	-0.021
	(0.13)	(-0.11)
Singapore	0.143	0.192
	(0.85)	(0.84)
Emerging Markets		
Malaysia	-0.049	-0.193
	(-0.33)	(-0.98)
China	0.065	-0.036

	(0.46)	(-0.19)
Indonesia	-0.115	-0.090
	(-0.83)	(-0.49)
Brazil	0.487	0.345
	(3.77)*	(4.41)*
Mexico	-0.027	0.061
	(-0.18)	(0.31)
South Africa	0.073	0.000
	(0.48)	(1.47)
South Korea	-0.023	-0.036
	(-0.17)	(-0.27)
Taiwan	-0.02	-0.238
	(-0.18)	(-1.33)
India	0.052	0.067
	(0.37)	(0.36)
Russia	0.057	0.116
	(0.37)	(0.57)
Columbia	-0.059	-0.016
	(-0.33)	(-0.06)
Chile	0.311	0.33
	(2.26)*	(2.10)*

Note: The biased reduction estimation is performed with bandwidth *m* equal to square root of the number of observation. The test is performed with r=1, and 2, r being the non-negative integer (additional regressor). The values in the parentheses represent corresponding significance level. *, * indicates significance at 1 % and 5 % level respectively.