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Stock return distribution in the BRICS

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Abstract

Stock returns in emerging market economies exhibit patterns that are distinctively different from developed countries: returns are noted to be highly volatile and autocorrelated, and long horizon returns are predictable. While these stylized facts are well established, the assumption underlying the distribution of returns is less understood. In particular, the empirical literature continues to rely on the normality assumption as a starting point, and most asset pricing models tend to overstretch this point. This paper questions the rationale behind this supposition and proceeds to test more formally for normality using multivariate joint test for skewness and kurtosis. Additionally, the paper extends the literature by examining a number of empirical regularities for Brazil, Russia, India, China and South Africa (the BRICS for short). Our main findings are that the distribution of stock returns for the BRICS exhibits peakedness with fatter and longer tails, and this is invariant to both the unit of measurement and the time horizon of returns. Volatility clustering is prevalent in all markets, and this decays exponentially for all but Brazil. The relationship between risk and return is found to be significant and risk premiums are prevalent in our sample.

JEL classification: F23; F36; G10; G30

Keywords: Normality; Return predictability; Leverage effect; Volatility clustering; Efficiency; Emerging markets

1. Introduction

Since Goldman Sachs economist, Jim O'neil coined the term BRIC in the early 2000s, the economies of Brazil, Russia, India and China have taken centre stage in both the global politics and economics. In 2010, South Africa joined the club, officially spreading the tentacles of the largest emerging market economies over four continents. By 2013, the BRICS accounted for almost 3 billion of the world's population, with a combined nominal GDP of US$16.039 trillion. About US$4 trillion of foreign reserves are held by the BRICS, with China alone accounting for more than a quarter.

Over the past few years, the performance of BRICS stock markets has been sterling. Data from Reuters (2012) shows that viewed in a 10 year horizon, the Morgan Stanley Capital International (MSCI) BRIC index returned a striking 450%, compared to the 320% and 98% returns on other emerging and developed markets respectively. Between 2001 and 2007 the MSCI's BRIC index returned over 500%, significantly outperforming other emerging markets. However, recent evidence shows that the hay days may be over soon. There have been slumps in the most recent period with losses of 8.6% in the past five years in dollar terms. There are also indications that China's impressive double digit growth spurt is fading. Brazil and South Africa's growth has been anaemic, and Russia faces problems in the oil and gas sector while reforms in India have been sluggish. The volatility in growth rates and stock market performance raises important questions pertinent to investments, portfolio diversification and the overall role of the BRICS in global economic growth. Will the BRICS assets continue to receive the attention they have enjoyed over the past decade? What is the nature of the risk return relationship in these markets? Questions such as these

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bother on the distributional patterns, volatility and predictability of stock returns as well as the efficiency of the BRICS. This article concerns itself with return distribution, and on the time series properties of stock returns. The paper extends the literature in two directions.

The first is methodological. Standard asset pricing models such as the mean variance model takes the normality of asset returns as given. Although this assumption has been pointed out to be highly unrealistic (see Mandelbroit, 1963; Rachev, 2003) even for developed markets, a significant amount of research continue to focus on the normality of returns as a starting point. This is not surprising since the computational intensity underlying alternative distributions is both time consuming and more daunting. More so, the properties of the normal distribution are sufficiently well known and studied in the literature. However, the consequence of relying on models of normal returns may lead to significant underestimation of the risk of investing in emerging markets, particularly if the distribution is skewed and fat tailed. This paper thus questions the over reliance on the normality assumption that exist in the extant literature on the distribution of returns in emerging markets. Departing from extant literature we employ a multivariate skewness and kurtosis test of Mardia (1970) and the joint skewness and kurtosis test of Henze and Zirkler (1990).

The second contribution is to extend the literature on the peculiarities of asset returns in the BRICS. A number of research efforts have been expended in understanding the return distribution of emerging markets generally, however, a lot remains to be learned about the BRICS stock markets efficiency in allocating scarce resources. Moreover, the most comprehensive study of the return distribution of emerging markets appeared nearly two decades ago (Bekaert et al., 1998). On the empirical regularities emerging markets are noted to have low/or negative correlations with the more developed world (see Harvey, 1995; Alagidede, 2010); emerging market economies offer returns that exceed industrial-market returns (Buckberg, 1995; Reuters, 2012). Both of these facts suggest that unexploited profit opportunities may exist. At the same time, emerging market returns tend to exhibit high volatility and autocorrelation, long run predictability and generally low levels of liquidity (Bekaert and Harvey, 1997; Aggarwal et al., 1999; Kasman et al., 2009; Blitz et al., 2013; Hull and McGroarty, 2014). These stylized features may signal market inefficiency and opportunities for profitable arbitrage. Understanding the dynamic behaviour of stock returns in the BRICS is crucial for portfolio managers, policy makers, and researchers. We contribute to this strand of the literature by accounting for return dynamics in different time horizons and currencies.

1.1. *Stylized facts of BRICS stock markets*

The key facts about BRICS stock markets are indicated in Table 1. For the sake of brevity, and in line with data availability, the World Development Indicators for the stock market variables are only reported for 2012. The market capitalization, turnover ratio and trading value are all expressed as a percentage of GDP. Market capitalization is the share price multiplied by the number of shares outstanding, and it is a rough benchmark for judging a company's net worth. The turnover ratio is derived by dividing the value of total shares by the market capitalization. While the total value traded ratio captures trading relative to the size of the economy, and the turnover ratio measures trading relative to the size of the stock market. In practice, the turnover ratio proxies the liquidity of the market: high turnover is an indicator of low transaction costs.

From Table 1, no single BRICS country dominates in terms of all indicators, unsurprisingly confirming the diversity of depth, performance and influence of the national stock exchanges. Judged by market capitalization, the Chinese market stands out. The Shenzen, Shanghai and Hong Kong stock markets had a market capitalisation of $3.7 trillion dollars at the end of 2012. The Shenzen stock exchange is overwhelmingly dominated by state owned enterprises which are the back bone of the Chinese economy, while the Shanghai is not fully opened to foreign investors. Brazil and India have market capitalisation of about $1.2 and $1.3 trillion as of 2012, respectively. In the BRICS, Russia and South Africa are the smallest markets using this indicator at $874 billion and $612 billion, respectively. In relation to the size of the domestic economy, however, South Africa dominates as seen from Table 1. The size of the stock market as a proportion of GDP is a whopping 159%. This gives a high value of shares traded as proportion of GDP in South Africa (81%) than any country in Table 1. Interestingly, China's stock market is 44% of GDP, slightly bigger than the Russian 43% but less than Brazils 54% and India's 68%. With the exception of South Africa and China, total value traded as a share of GDP is less than 40% as of 2012.

The number of listed domestic companies amounted to 5191 in India in 2012. This is about 15 times the number of companies in Brazil and South Africa and about 19 times the number of domestic companies listed in Russia's stock market. China comes second with 2494 companies. The most liquid of the BRICS stock markets is China (164%), followed by Russia (87%) and Brazil (67%). India and South Africa have a turnover ratio of about 54%.

2. Empirical strategy and data

The analysis of the data for this study follows three steps. First we examine the nature of the probability distribution of the index return series for the BRICS measured in both US dollars and local currency and for different holding periods: daily, weekly and monthly. While this analysis is an end in itself, it also offers important information relevant for selecting the appropriate statistical model for performing inference on the return generating process. To achieve this aim, we employ the Mardia (1970) skewness and kurtosis, and Henze and Zirkler (1990) test for joint skewness and kurtosis.

Tests and estimates based on the sample mean vector and sample covariance matrix have been shown to have poor efficiency properties when heavy tailed noise distributions are present in a data set. Mardia (1970, 1974 and 1980) pioneered measures of skewness and kurtosis, and demonstrated that functions of the third and fourth moments are asymptotically distributed as

Table 1
Facts about BRICS stock markets (2012).

	Market capitalization (Current US$)	Market capitalization (% of GDP)	Listed domestic companies	Total value traded (% of GDP)	Turnover ratio (%)
Brazil	$1.229 trn	54.60	353	37.05	67.88
Russia	$874 bn	43.41	276	36.34	87.64
India	$1.26 trn	68.60	5191	33.80	54.63
China	$3.69 trn	44.94	2494	70.82	164.44
South Africa	$612 bn	159.33	348	81.13	54.93

Source: Compiled from World Development Indicators of the World Bank (Online version).

chi-square and standard normal. By generalizing the univariate skewness and kurtosis to a multivariate setting, Mardia (1970) demonstrated that the power of the test is sufficiently improved. In the univariate case, standardized third and fourth moments b_1, b_2 are often used to indicate the skewness and kurtosis. For a random sample $x_1, \ldots, x_n$ from a p-variate distribution with sample mean vector $\bar{x}$ and sample covariance matrix S, Mardia defined the p-variate statistic as $b_{1,p} = ave_{i,j}[(x_i - \bar{x})^T S^{-1}(x_j - \bar{x})]^3$ and $b_{2,p} = ave_i[(x_i - \bar{x})^T S^{-1}(x_i - \bar{x})]^2$ respectively. The statistics $b_{1,p}$ and $b_{2,p}$ are functions of the standardized third and fourth moments respectively. Thus $b_{1,p}$ and $b_{2,p}$ are invariant under affine transformation. In the univariate case these reduce to the usual univariate skewness and kurtosis statistics b_1 and b_2. Mardia advocate using the skewness and kurtosis to test for multinormality as they are distribution free under normality. The skewness statistic is thus decomposed as

$$b_{1,p} = 6\sum_{j<k<1}[ave_i\{z_{ij}z_{ik}z_{il}\}]^2 + 3\sum_{j\neq k}[ave_i\{z_{ij}^2 z_{ik}\}]^2 + \sum_j [ave_i\{z_{ij}^3\}]$$

and the kurtosis is similarly

$$b_{2,p} = \sum_{j\neq k} ave_i\{z_{ij}^2 z_{ik}^2\} + \sum ave_i\{z_{ij}^4\}$$

Under multinormality, $b_{1,p}$ and $b_{2,p}$ are asymptotically normal and asymptotically independent and consequently the limiting distributions of $n(b_{1,p}/6)$ and $\sqrt{n}((b_{2,p} - p(p+2))/\sqrt{8p(p+2)})$ are a chi-square distribution with $p(p+1)(p+2)/6$ and a $N(0, 1)$ distribution respectively.

However, despite its widespread use the statistic has been found wanting in distinguishing well between 'skewed' and 'non-skewed' distributions (see Mecklin and Mundfrom, 2005). Thus it is possible to combine this statistic into an omnibus test to improve the power of the test. Consistent and invariant tests proposed by Epps and Pulley (1983) are an example. The Epps and Pulley (1983) statistic is based on

$$T = \int_{-\infty}^{\infty} |\Phi_n(t) - \hat{\Phi}_0(t)|^2 \, dG(t)$$

where $\Phi_n(t)$ is the empirical characteristic function, $\hat{\Phi}_0(t)$ is an estimate of the characteristic function of the normal distribution, and, $G(t)$ is a weight function. Henze and Zirkler (1990) proposed a multivariate extension to the test statistic above, namely

$$D_{n\beta} = \int_{\Re^d} |\Phi_n(t) - \hat{\Phi}_0|^2 \varphi_\beta(t)dt$$

where $\Phi_n(t)$ is the empirical characteristic function of the standardized observations, $\hat{\Phi}_0(t)$ is the characteristic function of a multivariate standard normal distribution, and $\varphi_\beta(t)$ is a kernel function. Henze and Zirkler (1990) use the density function of a $N_p(0, \beta^2 I_p)$ random vector ($\beta \in \Re$) in deriving their test statistic and they show that the test statistic has a lognormal asymptotic distribution and derive a closed form expression for $D_{n\beta}$. Using various values of β Henze and Zirkler (1990) conducted a simulation study to compare their statistic with others, including Mardia's (1970) multivariate measures of skewness and kurtosis. The choice of $\beta = 0.5$ in a simulation exercise can produce a powerful test against alternative distributions with heavy tails, and in comparison with other kinds of distributions: independent marginals, mixtures of normal distributions, and spherically symmetric distributions, the multivariate joint test for skewness and kurtosis is noted to have good power properties, and more reliable than those obtained from univariate descriptive statistics (see Henze and Zirkler, 1990).

The second step involves testing for the presence of autoregressive conditional heteroscedasticity (ARCH) in the mean of the index returns for the BRICS. Again, whiles the presence of ARCH effect in the mean of the return series offer important information about the return behaviour and efficiency of markets, it also offers vital information in selecting the appropriate model for the return generating process.

In the third step, we estimate a statistical model that appropriately captures the essential features of the return generating process.

The rests of this section is devoted to the description of the econometric or estimation technique adopted, and a brief description of our data. To begin with, we assume that the log of the stock price index follows a random walk with a drift. That is:

$$\ln P_t = \mu + \ln P_{t-1} + \varepsilon_t \quad (1)$$

Eq. (1) implies the following expression for the return generating process (RGP):

$$R_t = \ln P_t - \ln P_{t-1} = \mu + \varepsilon_t \quad (2)$$

In many applications, it turns out that the effect of positive news tends to differ from negative news of equal size, on average. To account for this, we adopt the exponential generalized autoregressive conditional heteroscedasticity in the mean (EGARCH-M) of the return series. We also augment the standard EGARCH-M specification with *ARMA*(*p*,*q*) model. The specific functional form of the model adopted for this study is:

$$R_t = \mu + \sum_{i=1}^{p} \beta_i R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varphi h_t + \varepsilon_t \quad (3)$$

$$\varepsilon \,|\eta_{t-1} \approx t \cdot d(0, h_t, v_t) \quad (4)$$

With the above specification, R_t is the market return and μ is the expected return, h_t is the risk premium (volatility), ε_t is the error term that we assume to have a student-T distribution due to the skewness and excess kurtosis of each of the series, while p and q are the optimal lag orders for the autoregressive (AR) and moving average (MA) terms respectively. The inclusion of the risk premium term in the mean Eq. (4) is to model the relationship between expected return and risk. A significant and positive φ implies that expected return is positively related to risk and a negative relation if the reverse is true.

Additionally, to account for possible asymmetry of news on return-risk relationship, we apply the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model proposed by Nelson (1991), in which the volatility (h_t) as presented in Eq. (3) is express as;

$$\ln(h_t) = \omega + \alpha_1 z_{t-1} + \gamma_1(|z_{t-1}| - E(|z_{t-1}|) + \delta_1 \ln(h_{t-1}) \quad (5)$$

This specification is much more flexible since we do not need to explicitly impose non-negativity restrictions on the parameters in the ARCH and GARCH terms in the model. The reason is that the log transformation ensures that the variance is non-negative and therefore free from the problems of possible negative variance as in the case of the standard GARCH models. The α_1 is the parameter that capture leverage effect, implying that a significant positive α_1 is an indication of positive innovations having more effects on returns than negative innovations, γ_1 is the symmetry term and δ_1 the GARCH term, while ω is the constant term in the volatility equation.

2.1. Data sources and descriptions

The data employed in this paper is the Morgan Stanley Capital International (MSCI) indices for emerging markets, focussing mainly on Brazil, Russia, India, China and South Africa. We use the MCSI World Index as a proxy for the World portfolio. The MSCI data for emerging markets captures large and mid-capitalisation stocks and it covers roughly 85% of the free float-adjusted market capitalization in each country. The data is from the period January 1995 to May 2014. For completeness we use daily, weekly and monthly data reported in both US dollars and local currency values. This allows us to compare the behaviour of returns across different time horizons and to examine the impact of exchange rate variations on stock returns. All the series under consideration are obtained from Thomson DataStream. Following Pukthuanthong and Roll (2009), we filter returns to purge holidays and nontrading days.

3. Emerging market return distribution

In this section we examine the distribution of the return series. First we look at the summary statistics from the return series. Next we test for the presence of skewness and kurtosis in the returns (both in US dollars and local currency) on daily, weekly and monthly frequencies. Summary statistics on all the series that we examined are reported in the Appendix. Judging by the Jarque–Bera statistic, the reported summary statistics on the return series indicate non-normal distribution for all the series both in US dollars and local currency for daily, weekly and monthly holding periods. In almost all the cases examined here, the skewness coefficient is negative with the exceptions being daily dollar returns for China and daily returns in local currency units for Brazil and China. Thus the implication from the summary statistics suggest that the probability distributions of BRICS returns for daily, weekly and monthly holding periods are negatively skewed, indicating that the left tails of the distribution are either longer or fatter (or both) than the right tail.

Following the clue from the summary statistics, we undertake a formal statistical test to produce evidence on the skewness and excess kurtosis of the return series for the BRICS. The results are reported in Table 2 (for daily returns), Table 3 (for weekly returns) and Table 4 (for monthly returns).

Three different tests are employed – Mardias kewness test, Mardia kurtosis test and Henze–Zirkler joint skewness and kurtosis test. As can be seen from the upper panel of Table 2, the null hypothesis that the skewness coefficient is not statistically different from zero for the daily return series is flatly rejected by the Mardia skewness test for Brazil, Russia, South Africa and the World. In the case of India and China, however, the null hypothesis is not rejected at the conventional level of statistical significance. There is strong evidence of excess kurtosis (leptokurtosis) in the daily stock return series for the BRICS market indexes as well as the World stock market index. The Mardia kurtosis test for excess kurtosis in the return series flatly rejected the null hypothesis in all the cases at 1% level of statistical significance. The strong evidence of excess kurtosis in the daily dollar return series is confirmed by Henze–Zirkler joint test for the evidence of skewness and excess kurtosis. The null hypothesis is rejected at the 5% level of statistical significance or lower. The evidence reported here gives strong indication that the probability distribution of the daily dollar stock returns for the BRICS exhibits peakedness with fatter and long tails. Jointly, these indicate that the probability distribution is non-normal, and special attention needs to be taken when performing statistical inference on them.

This conclusion is invariant to the unit in which the returns are measured. This is confirmed by the results reported in the lower panel of Table 2 where the null hypotheses of no skewness, no kurtosis and no joint skewness and kurtosis in daily stock returns in local currency units are all rejected at conventional level of significance. It has been pointed in the extant literature that the normality assumption on the probability distribution of

Table 2
Skewness and Kurtosis test on daily returns.

	Brazil	Russia	India	China	South Africa	World
Daily US Dollar Returns						
Skewness	0.0094	0.9947	0.0029	0.0008	0.1759	0.1376
	[7.946]	[168.3]	[2.408]	[0.697]	[148.5]	[116.16]
	(0.0048)	(0.0000)	(0.1207)	(0.4038)	(0.0000)	(0.0000)
Kurtosis	10.5850	14.8363	9.6360	8.7725	8.4823	10.8188
	[12,127.2]	[29,531.3]	[9282.4]	[7023.9]	[6335.3]	[12,886.4]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Joint	81.462	166.91	71.39	114.81	61.2102	91.1044
	[96.73]	[126.78]	[91.64]	[110.59]	[85.881]	[101.15]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Daily Local Currency Returns						
Skewness	0.7469	1.2042	0.2847	0.2967	0.5797	2.2989
	[29.637]	[47.779]	[11.296]	[11.771]	[23.0000]	[91.214]
	(0.0000)	(0.0000)	(0.0008)	(0.0006)	(0.0000)	(0.0000)
Kurtosis	5.7088	7.4317	4.8019	4.1349	5.0858	8.4045
	[70.931]	[189.854]	[31.386]	12.451	[42.054]	[282.352]
	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)
Joint	2.5986	3.912	1.6422	3.0689	1.7083	5.6917
	[10.005]	[14.423]	[6.008]	[11.680]	[6.313]	[19.178]
	(0.0016)	(0.0001)	(0.0142)	(0.0006)	(0.0120)	(0.0000)

Note: In [] are the chi squared statistics and () are the probability values.

stock returns are more likely to be violated in high frequency data than a low one. We therefore repeat the above skewness and kurtosis test on weekly and monthly stock returns for the BRICS as well as the World. Again, we consider both the returns measured in local currency units and the US dollar. The findings on the weekly returns series concerning skewness and kurtosis of their underlying probability distributions are not at variance with those reported on daily return series.

With the exception of Russia where the null hypothesis of no skewness is not rejected for both returns in the local currency units and US dollar weekly series, the null hypothesis of no skewness in the probability distribution of returns is rejected for the remaining BRICS weekly return series. In terms of kurtosis, the null hypothesis is rejected for all the weekly return series measured in terms of both the US dollar and local currency units.

The Henze–Zirkler joint test for skewness and kurtosis in the probability distribution of weekly BRICS returns (both local currency and US dollars) rejected the null hypothesis flatly for all the BRICS market as well as the World stock market returns.

Table 3
Skewness and Kurtosis test on weekly stock returns.

	Brazil	Russia	India	China	South Africa	World
Weekly US Dollar Returns						
Skewness	0.4231	0.0156	0.1361	0.0722	0.0372	1.2880
	[71.723]	[2.654]	[23.073]	[12.236]	[6.302]	[218.326]
	(0.0000)	(0.1033)	(0.0000)	(0.0000)	(0.0121)	(0.0000)
Kurtosis	7.0750	8.5842	5.2467	5.9561	7.6655	12.8531
	[699.5]	[1313.6]	[212.639]	[368.1]	[916.942]	[4089.623]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Joint	11.6893	28.2706	3.9810	10.9712	13.2744	13.4321
	[31.589]	[51.143]	[14.085]	[30.365]	[34.115]	[34.355]
	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Weekly Local Currency Returns						
Skewness	0.29887	0.0108	0.10997	0.0761	0.2023	1.0809
	[50.627]	[1.824]	[18.640]	[12.891]	[3.430]	[183.207]
	(0.0000)	(0.1769)	(0.0000)	(0.0003)	(0.0640)	(0.0000)
Kurtosis	6.8719	9.1566	5.2756	5.9893	6.1066	12.2076
	[631.514]	[1596.713]	[218.146]	[376.418]	[406.560]	[3571.348]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Joint	11.2145	33.7756	5.0106	11.2019	11.4684	12.1046
	[30.786]	[55.649]	[17.237]	[30.764]	[31.218]	[32.273]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000)

Note: In [] are the chi squared statistics and () are the probability values.

Table 4
Skewness and Kurtosis test on monthly stock returns.

	Brazil	Russia	India	China	South Africa	World
Monthly US Dollar Returns						
Skewness	1.2993	1.1155	0.4244	0.2909	2.1596	2.8078
	[51.553]	[44.258]	[16.837]	[11.543]	[85.688]	[111.408]
	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0000)	(0.0000)
Kurtosis	6.9145	7.0115	5.1774	4.1089	10.0213	9.7901
	[148.126]	[155.554]	[45.829]	[11.887]	[476.548]	[445.684]
	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)
Joint	2.4569	3.5946	1.2176	3.0417	2.2856	5.1941
	[9.462]	[13.443]	[3.949]	[11.610]	[8.785]	[17.956]
	(0.0021)	(0.0002)	(0.0469)	(0.0007)	(0.0030)	(0.0000)
Monthly Local Currency Returns						
Skewness	1.2993	1.1155	0.4244	0.2909	2.1596	2.8078
	[51.553]	[44.258]	[16.837]	[11.543]	[85.688]	[111.408]
	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0000)	(0.0000)
Kurtosis	6.9145	7.0115	5.1774	4.1089	10.0213	9.7901
	[148.126]	[155.554]	[45.829]	[11.887]	[476.548]	[445.684]
	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)
Joint	2.4569	3.5946	1.2176	3.0417	2.2856	5.1941
	[9.462]	[13.443]	[3.949]	[11.610]	[8.785]	[17.956]
	(0.0021)	(0.0002)	(0.0469)	(0.0007)	(0.0030	(0.0000)

Note: In [] are the chi squared statistics and () are the probability values.

The implication here is that the weekly return series inherits the fatter and longer tails and peakedness that characterized the probability distribution of daily stock returns, at least for the BRICS and the World stock market as a whole.

We now consider the tail and peak behaviour of the probability distribution of monthly index returns for the BRICS and the World Stock markets. In the preceding paragraph, we arrived at the conclusion that weekly return series inherits the properties of the distribution of daily returns. It is thus important to ask whether monthly returns also inherits the properties of the probability distribution of weekly returns and hence those of daily returns. We thus search for evidence of skewness and kurtosis in monthly returns for the BRICS in both dollar series and local currency series. The results are reported in Table 4. Consistent with our results on daily and weekly returns, the Mardia tests for skewness and kurtosis rejected the null hypothesis of no skewness and no kurtosis in the probability distribution of monthly stock returns. Henze–Zirkler joint test for skewness and kurtosis in the probability distribution of monthly returns also rejected the null hypothesis in all cases. This conclusion is not sensitive to the unit in which monthly returns are measured (either in US dollars or local currency units). Thus the evidence of non-normality in the distribution of BRICS index and World market index returns is robust. In line with Bekaert et al. (1998) we are able to establish that the BRICS stock returns exhibit time varying skewness and kurtosis. The underlying structure of the BRICS: their potential for large growth swings, susceptibility to regulatory and political changes, and continued integration into the global economic and financial system may thus lead their stock returns to deviate significantly from the Gaussian assumption. As a result, any statistical inference which relies on the normality of the distribution of returns has the potential of making erroneous conclusions.

4. Volatility, predictability and risk-return relationship

In this section we estimate and report evidence on the volatility, predictability and risk-return relationships for the BRICS index returns. Due to the similarities in the distribution of the return series for the daily, weekly and monthly holding periods, we only focus on modelling daily return behaviour. To begin with, we test for the presence of ARCH effects in the mean of the daily returns using the Lagrange multiplier (LM) test. The results are reported in Table 5.

The results of the Lagrange multiplier (LM) test for the presence of ARCH effects in the mean of BRICS index return series flatly rejected the null hypothesis of no ARCH effects at 1% level of statistical significance for all the countries. This conclusion is invariant to whether the BRICS index returns are measured in the local currencies or in United States dollars. The invariance of the presence of ARCH effects in the mean of the returns for the BRICS suggests that exchange rate movements have not affected BRICS index returns volatility; an empirically testable proposition.

The variance is time dependent and thus need to be accounted for in any statistical model aimed at capturing the return generating process of these countries.

Given the evidence of the presence of autoregressive conditional heteroscedasticity in the mean of BRICS index returns, we proceed to model the mean and the conditional variance of each of the BRICS market indexes using $ARMA(p, q) - EGARCH(m, n) - M$. The results of our estimates are reported in Table 6 (for daily returns measured in US dollars) and Table 7 (for returns measured in local currency. The model diagnostic statistics reported at the lower parts of Tables 6 and 7 indicate that the estimated mean and conditional variance equations were correctly specified. In particular, the Ljung-Box *Q-statistic* at both

Table 5
Lagrange multiplier test for ARCH effects in BRICS daily stock returns.

	Brazil	Russia	India	China	South Africa
Lagrange Multiplier Test for ARCH effect in the Mean of Daily US dollar Returns					
Lags = 1	222.26 (0.000)	549.76 (0.000)	136.23 (0.000)	361.35 (0.000)	289.60 (0.000)
Lags = 5	1079.97 (0.000)	641.59 (0.000)	317.96 (0.000)	736.58 (0.000)	638.81 (0.000)
Lags = 10	1167.28 (0.000)	732.62 (0.000)	413.28 (0.000)	802.37 (0.000)	827.59 (0.000)
Lags = 20	1235.45 (0.000)	871.65 (0.000)	449.68 (0.000)	910.10 (0.000)	988.58 (0.000)
Lagrange Multiplier Test for ARCH effect in the Mean of Daily Local Currency Returns					
Lags = 1	189.52 (0.000)	571.66 (0.000)	183.34 (0.000)	361.33 (0.000)	330.97 (0.000)
Lags = 5	563.23 (0.000)	662.92 (0.000)	385.87 (0.000)	739.24 (0.000)	547.31 (0.000)
Lags = 10	621.29 (0.000)	753.76 (0.000)	463.03 (0.000)	804.67 (0.000)	589.44 (0.000)
Lags = 20	658.83 (0.000)	893.91 (0.000)	498.62 (0.000)	912.78 (0.000)	639.78 (0.000)

Note: The test statistic for the LM test follows a chi square distribution. The numbers reported in the above table are the chi squared statistics with () housing the probability values.

lags 11 and 25 did not reject the null hypothesis that the mean equation is correctly specified for all the BRICS index returns. Also, the Ljung-Box *Q-squared statistic* failed to reject the null hypothesis that the conditional variance equation is correctly specified. The estimated $ARMA(p, q) - EGARCH(m, n) - M$ adequately captures the conditional mean and variance of the return generating process for the BRICS. We therefore turn to the interpretation of the estimated parameters.

Table 6
Estimated ARMA-EGARCH-M model of Daily Returns in Dollars.

	Brazil	Russia	India	China	South A	World
μ	0.125	0.248***	0.0125	−0.0727	−0.332	0.0871***
	(1.49)	(4.27)	(0.09)	(−1.32)	(−0.98)	(8.26)
ARCHM						
φ	0.0237	−0.00848*	0.0722	0.0220*	0.126	−0.0251**
	(1.90)	(−2.57)	(1.85)	(2.11)	(1.21)	(−2.74)
ARMA						
AR(1)	0.999***	−0.0126	0.990***	0.998***	−0.00115	0.0573***
	(2710.22)	(−1.10)	(4905.07)	(633.92)	(−0.08)	(9.54)
AR(2)		0.000151	0.00981***		0.00808	0.0272**
		(0.02)	(48.78)		(0.68)	(2.79)
AR(3)					−0.0111	
					(−0.98)	
MA(1)	−0.997***		−0.997***	−0.997***		−0.0646***
	(−1617.12)		(−1370.94)	(−573.32)		(−10.99)
ARCH						
α	0.0221	0.0520	0.0226	0.0147	0.0229	−0.0135
	(1.10)	(1.26)	(0.67)	(0.44)	(0.77)	(−0.48)
γ	0.129***	0.362***	0.117**	0.235***	0.100***	0.156***
	(4.52)	(5.40)	(2.75)	(4.68)	(3.35)	(4.06)
δ_1	0.815***	0.135	0.0166	0.189	−0.00775	−0.267
	(28.66)	(0.77)	(0.05)	(1.50)	(−0.01)	(−1.65)
ω	0.352***	2.631***	1.209**	1.416***	1.187	0.176
	(6.85)	(4.84)	(3.20)	(6.25)	(0.87)	(1.86)
N	5059	5059	5059	5059	5059	5059
AIC	21,709.7	23,600.2	19,077.8	20,080.7	19,084.4	13,097.5
BIC	21,768.4	23,658.9	19,143.1	20,139.5	19,149.7	13,162.8
LBQ(11)	15.702	6.412	16.463	9.342	17.199	12.288
	[0.152]	[0.844]	[0.124]	[0.590]	[0.102]	[0.342]
LBQ(25)	27.412	32.808	33.033	30.928	29.527	28.546
	[0.335]	[0.135]	[0.130]	[0.191]	[0.242]	[0.283]
LBQ^2(11)	14.460	6.424	16.267	9.204	16.692	11.300
	[0.208]	[0.843]	[0.131]	[0.603]	[0.117]	[0.418]
LBQ^2(25)	26.749	32.161	32.592	29.291	28.983	27.795
	[0.368]	[0.153]	[0.141]	[0.251]	[0.264]	[0.317]

t statistics in parentheses and the numbers in square brackets are the *p*-values, LBQ is the Ljung-Box statistics for serial correlation and LBQ^2 is the Ljung-statistics for ARCH effect, with the lags used in the parentheses.

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 7
Estimated ARMA-EGARCH-M model for Daily Returns in Local Currency.

	Brazil	Russia	India	China	South A	World
μ	-0.121^{***}	0.197^{**}	0.0537	-0.0837^{***}	0.138	0.103^{***}
	(−10.43)	(2.75)	(0.51)	(−18.55)	(0.94)	(6.53)
ARCHM						
φ	0.0460^{***}	−0.00429	0.0603	0.0184^{***}	0.0462	-0.0391^{**}
	(11.57)	(−1.36)	(1.66)	(16.58)	(0.56)	(−2.77)
ARMA						
AR(1)	0.00760	−0.0105	0.993^{***}	-0.987^{***}	1.013^{***}	−0.00778
	(0.63)	(−0.85)	(4511.98)	(−835.39)	(7265.27)	(−0.60)
AR(2)		0.00416	0.00611^{***}		-0.00813^{***}	0.0230^{*}
		(0.45)	(26.74)		(−64.04)	(2.57)
AR(3)					-0.00542^{***}	
					(−52.21)	
MA(1)			-0.997^{***}	0.985^{***}	-0.997^{***}	
			(−1324.60)	(1164.69)	(−877.71)	
ARCH						
α	0.00950	0.0863	0.0345	0.0165	0.0297	−0.000248
	(0.52)	(1.77)	(0.90)	(0.50)	(1.19)	(−0.01)
γ	0.145^{***}	0.501^{***}	0.141^{**}	0.240^{***}	0.0661	0.170^{***}
	(4.47)	(5.09)	(3.11)	(4.36)	(1.72)	(4.42)
δ_1	0.831^{***}	0.246	0.0135	0.198^{***}	−0.356	-0.413^{**}
	(107.91)	(1.95)	(0.04)	(8.29)	(−0.70)	(−2.87)
ω	0.270^{***}	2.618^{***}	1.045^{**}	1.406^{***}	0.699^{**}	0.204
	(28.62)	(5.60)	(2.97)	(37.66)	(2.68)	(1.71)
N	5059	5059	5059	5059	5059	5059
AIC	19,662.8	23,178.2	18,127.4	20,065.9	15,924.0	12,748.7
BIC	19,715.0	23,236.9	18,192.7	20,124.7	15,995.8	12,807.5
LBQ(11)	17.130	7.277	18.724	10.798	8.589	11.499
	[0.104]	[0.776]	[0.066]	[0.460]	[0.659]	[0.402]
LBQ(25)	32.443 [0.145]	30.882	33.914	35.870	30.052	28.580
		[0.192]	[0.109]	[0.073]	[0.222]	[0.281]
$LBQ^2(11)$	14.984	7.333	18.807	10.279	8.402	10.581
	[0.183]	[0.771]	[0.064]	[0.505]	[0.676]	[0.479]
$LBQ^2(25)$	30.157	30.687	34.308	33.378	29.985	27.879
	[0.218]	[0.199]	[0.101]	[0.121]	[0.224]	[0.313]

t statistics in parentheses and the numbers in square brackets are the *p*-values, LBQ is the Ljung-Box statistics for serial correlation and LBQ^2 is the Ljung-statistics for ARCH effect, with the lags used in the parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

According to the results reported in Table 6, the expected daily index return is statistically not different from zero for Brazil, India, China and South Africa. However, the index for Russia and the World index promise a positive return. The estimated mean return for Russia is 0.248 and it is statistically significant at 1% level. For the World index return, the estimated mean is 0.078 which is also statistically significant at 1% level. When returns are measured in local currency however, the expected daily index returns for Brazil and China are negative and statistically significant at 1% level. The estimated expected return for Brazil and China are −0.121 and −0.084 respectively. On the contrary, Russia and the World index returns are both positive and statistically significant on the average, when returns are measured in local currency units. For Russia and the World index, the estimated expected daily index returns are 0.197 (which is statistically significant at 5% level) and 0.103 (which is statistically significant at 1% level) respectively. The estimated expected daily index returns in local currency units are, however, not statistically different from zero for India and South Africa. Thus, for India and South Africa the daily index return is zero and positive for Russia, irrespective of the unit in which returns are measured.

One implication of the capital asset pricing model (CAPM) is that expected return and risk are related positively. For a rational risk-averse investor to take on an additional risk, he must be compensated with additional return. We confront this prediction of CAPM with BRICS index returns data. The risk-return relationship parameter is captured by the coefficient on *varphi* (φ) of the ARCHM part of the results reported in Tables 6 and 7. From Table 6 the estimated coefficient on the risk variable (appropriately interpreted as the *risk premium*) is positive for all the BRICS except Russia and the World index, for daily dollar returns. In sharp contrast with the predictions of the CAPM, the coefficient on the conditional variance in the mean equation which captures the relationship between risk and return are negative and statistically significant for Russia and the World. This is a violation of rational behaviour of risk-averse investors in equity markets. However, the estimated risk-return relationship is only statistically significant for Russia, China (10% level of significance) and the World (5% level of significance). With returns measured in local currency however, the estimated coefficient on the conditional variance in the mean equation is positive and statistically significant for Brazil and China but negative and significant for the World. However, given the negative mean local currency return for Brazil and China, the estimated positive relative risk aversion coefficients implies a negative relationship between risk and return, a finding which is inconsistent with the CAPM. The World local currency index return also violates the predicted positive risk-return relationship by the CAPM since the estimated mean return is positive while the estimated risk aversion parameter is negative and statistically significant.

We now turn to the question of predictability of daily index returns both in US dollars and local currency units and the implications thereof for the efficiency of BRICS markets. In well-functioning equity markets the prices of the securities traded act as though they fully reflect all available information and react instantaneously and in an unbiased fashion to new information (Fama, 1970, 1991). If this were not the case, it would be possible to obtain riskless return, casting doubts about the ability of the stock market to efficiently allocate capital. The weak form of the efficient markets hypothesis thus precludes any predictability on the basis of past information (see Fama, 1991). Are BRICS stock returns predictable?

This question can be answered from the $ARMA(p,q)$ component of the estimated $ARMA(p,q) - EGARCH(m,n) - M$ reported in Tables 6 and 7. According to the results reported in Table 6, the coefficient on the AR(1) is positive and statistically significant at 1% level for Brazil, India, China and the World index daily returns. Not only are these coefficients statistically significant, but also economically given the large size of the coefficients. For instance, the coefficient AR(1) are 0.999, 0.990, 0.998 and 0.057 for Brazil, India, China and the World index respectively. Interestingly, this sub group for the BRICS markets also showed negative and statistically significant coefficient on the first lag of the moving average (MA) component of the estimated $ARMA(p,q) - EGARCH(m,n) - M$. The estimated coefficient of the first lag of the shock to the mean process is −0.997 for Brazil, −0.997 for India and −0.997 for China. The implication from this is that past information about returns (prices) have predictive power on current and future returns(prices), a sharp contrast to the weak-form efficiency hypothesis. In the case of Russia and South Africa, there is no evidence that past returns and shocks to return prove any information in predicting current and future returns(prices). Does predictability necessarily imply inefficiency, and do stock prices in the BRICS reflect a rational assessment of fundamental values? Our answer is that without a notion of the model of return generation one cannot draw definite conclusions on the time series patterns alone. To this end we side with the theoretical conclusions of LeRoy (1973) and Lucas (1978) that rational expectations equilibrium prices need not form a martingale sequence.

Measuring returns using local currency series changes the results for Brazil and South Africa. In the case of Brazil neither past returns nor shocks to it offer any predictive power on current and future returns. This is in sharp contrast with the finding obtained when we measure returns in US dollars. For South Africa there is positive and statistically significant AR (1) and a negative and statistically significant MA(1) effect in the return generating process. This implies that past returns and past shocks to returns can be used to predict current and future daily Rand returns in the South African stock market. This finding may suggest the existence of profitable arbitrage. China, India and the World index are predictable, but this is invariant to whether returns are measured in local currency or US dollars. The predictability of BRICS returns seem to concur with similar studies on emerging markets (see for example Cooper, 1982; Darrat, 1990; Errunza and Losq, 1985), which examined the weak form version of the efficient markets hypothesis. The presence of first order first-order serial correlation in stock prices shows that information may not be fully incorporated in security prices. Dailami and Atkin (1990) argue that positive serial correlation may result in slow incorporation of new information, insider trading, or infrequent trading. There may be barriers to the dissemination of information, and companies appear to divulge less information with a greater time lag than is the norm. On the other hand, negative serial correlations may signal thin trading and subject to speculative influences.

4.1. Volatility persistence

Volatility persistence in the return series for each of the countries is described by both α_1 and δ terms in Tables 6 and 7. The parameter α_1 represent the lagged squared residuals from the EGARCH-M model, while δ is the lagged conditional variance term in the EGARCH model. Volatility is said to be persistent if the sum of the two volatility terms is close to unity, less persistent if less than unity and explosive if greater than unity. In both return series (in dollars and local currency) as reported in Tables 6 and 7, we find strong indication of volatility persistence for Brazil, the magnitude of the persistence terms sum-up to close to unity (0.944 and 0.976 for returns in dollars and local currency, respectively). We find less volatility persistence in the return series for all the other countries and also the World index return, irrespective of the unit of currency (dollars or local currency). The implication of these results is that, all the BRICS countries (with the exception of Brazil) show no evidence of long-memory in their respective return series. This means that shocks to volatility tend to decay very quickly, implying that previous volatility do not have a strong predictive power on current volatility. These results are, however, conditional on the model specification and the distribution assumption made in the estimation. Since all descriptive statistics and normality test along with testing for the effect of autoregressive conditional heteroscedasticity pointed towards the model used in estimating the parameters presented in Tables 6 and 7, these results are very satisfactory.

4.2. Asymmetry in volatility

An avalanche of empirical research in emerging market returns distribution point to significant leverage effect, where higher volatility tend to follow negative returns (see Alagidede, 2011 and references therein). Asymmetries in the distribution of returns may arise either because of shocks to systematic risk factors that affect the cross section of returns, or because of country-specific shocks. This is taken up in the results reported in Tables 6 and 7. The evidence reveals a positive leverage effect for all return series (both in dollars and local currency), except South Africa which is insignificant. These results are confirmed by the misspecification test of Ling and McAleer (2000) and McAleer et al. (2007) (results reported in the Appendix) that the asymmetric EGARCH-M model best fit the BRICS data, and account for the volatility process well.

These results thus contravene the findings of Bekaert and Harvey (1995) and Bekaert and Harvey (1997) who do not find support for leverage effects in emerging markets.

5. Conclusion

This paper examined stock returns distribution in the biggest emerging market economies. Previous research has established that standard asset pricing models consistently fail to account for all the peculiarities of emerging markets returns. For instance, returns are noted to be highly volatile and non-normally distributed. Long horizon returns are predictable while there is significant autocorrelation in returns. After over two decades of research in emerging market economies, the issue of return distribution is far from settled. New data and empirical techniques, coupled with faster growth and increasing importance of emerging markets allow us to re-examine the distribution of stock returns for Brazil, Russia, India, China and South Africa for the period 1995–2014.

Using a multivariate joint test for skewness and kurtosis, and accounting for risk *premia* and conditional heteroscedasticity we arrived at the following findings: (a) the distribution of stock returns for the BRICS exhibits peakedness with fatter and longer tails. This is invariant to both the unit of measurement and the time horizon in which returns are studied. We argue that the underlying structure of the BRICS, particularly their potential for large growth swings, susceptibility to regulatory and political changes may lead their stock returns to deviate significantly from the Gaussian assumption and this ought to be incorporated in any inferences on return distribution. (b) While the stock markets of China and India are predictable irrespective of unit of measurement, return predictability for Brazil and South Africa are conditional upon whether we are looking at local currency or US dollar returns. Without an explicit model of the price generating process it is difficult to judge the weak form (in) efficiency of these markets on the basis of the time series properties alone. (c) All markets exhibit volatility clustering, and while this decays for most markets, it tends to be persistent for Brazil. Thus although shocks to current volatility may perpetuate through time, there is no evidence of long memory. (d) The so-called leverage effect is confirmed for all but South Africa, while the risk-return relationship is dynamically related to individual country and model specification.

Appendix A. Summary statistics of BRICS returns

	Brazil	Russia	India	China	South Africa	World
Daily US Dollar Returns						
Mean	0.023	0.039	0.024	−0.003	0.020	0.020
Median	0.058	0.060	0.021	0.003	0.076	0.068
Maximum	17.335	24.220	19.486	14.044	12.353	9.097
Minimum	−18.323	−31.013	−12.041	−14.442	−13.566	−7.325
Std. Dev.	2.318	2.992	1.738	1.971	1.726	0.993
Skewness	−0.097	−0.447	−0.053	0.029	−0.419	−0.371
Kurtosis	10.585	14.836	9.636	8.772	8.482	10.819
Jarque–Bera	12,135.07[0.000]	29,699.48[0.000]	9284.83[0.000]	7024.63[0.000]	6483.65[0.000]	13,002.46[0.000]
Daily Local Currency Returns						
Mean	0.042	0.040	0.036	−0.003	0.038	0.019
Median	0.000	0.061	0.000	0.000	0.013	0.068
Maximum	24.734	24.220	16.423	14.036	6.750	8.720
Minimum	−14.217	−31.013	−12.050	−14.457	−12.208	−7.156
Std. Dev.	1.923	2.928	1.588	1.969	1.253	0.960
Skewness	0.351	−0.462	−0.133	0.025	−0.406	−0.337
Kurtosis	15.365	15.834	9.392	8.811	8.249	10.360
Jarque–Bera	32,334.44[0.000]	34,900.44[0.000]	8626.06[0.000]	7118.92[0.000]	5947.81[0.000]	11,515.55[0.000]
Weekly US Dollar Returns						
Mean	0.125	0.196	0.124	−0.011	0.099	0.101
Median	0.422	0.447	0.364	0.234	0.356	0.321
Maximum	25.617	44.899	18.366	22.536	27.601	11.636
Minimum	−33.056	−31.698	−21.879	−24.336	−18.855	−22.381
Std. Dev.	5.322	7.100	3.950	4.619	3.907	2.375
Skewness	−0.650	−0.125	−0.369	−0.269	−0.193	−1.135
Kurtosis	7.075	8.584	5.247	5.956	7.666	12.853
Jarque–Bera	770.805 [0.000]	1316.244 [0.000]	235.577[0.000]	380.276[0.000]	923.208[0.000]	4306.687 [0.000]

Appendix A (*Continued*)

	Brazil	Russia	India	China	South Africa	World
Weekly Local Currency Returns						
Mean	0.221	0.200	0.185	−0.011	0.191	0.096
Median	0.440	0.448	0.434	0.230	0.296	0.323
Maximum	19.189	44.916	13.660	22.422	16.264	10.736
Minimum	−22.529	−31.698	−19.000	−24.341	−13.454	−21.318
Std. Dev.	4.120	6.946	3.557	4.609	2.840	2.287
Skewness	−0.547	−0.104	−0.332	−0.276	−0.142	−1.040
Kurtosis	6.872	9.157	5.276	5.989	6.107	12.208
Jarque–Bera	681.831	1598.525	236.676	389.233	409.969	3753.445
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Monthly US Dollar Returns						
Mean	0.552	0.945	0.564	−0.008	0.478	0.451
Median	2.027	3.095	1.397	1.240	1.263	1.080
Maximum	24.042	42.580	28.276	30.669	24.838	11.916
Minimum	−61.139	−72.397	−43.462	−36.550	−54.335	−31.643
Std. Dev.	10.929	16.065	9.314	10.156	8.513	5.232
Skewness	−1.140	−1.056	−0.651	−0.539	−1.470	−1.676
Kurtosis	6.915	7.011	5.177	4.109	10.021	9.790
Jarque–Bera	198.365	198.685	62.238	23.136	560.055	554.251
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Monthly Local Currency Returns						
Mean	0.967	0.961	0.832	−0.007	0.867	0.437
Median	1.651	2.715	1.395	1.250	1.370	1.237
Maximum	20.928	42.580	26.534	30.705	16.065	13.365
Minimum	−38.265	−71.604	−34.906	−36.677	−23.775	−26.982
Std. Dev.	8.059	15.652	8.315	10.147	6.004	4.987
Skewness	−0.864	−1.097	−0.534	−0.545	−0.761	−1.516
Kurtosis	5.709	7.432	4.802	4.135	5.086	8.405
Jarque–Bera	99.811	236.415	42.394	23.922	64.468	371.243
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Appendix B. Test for non-nested models

The Ling and McAleer (2000) and McAleer et al. (2007) test is a testing procedure for non-nested models, for instance between EGARCH and GARCH models. Suppose our proposed model is the EGARCH and we want to compare that with the GJR-GARCH model, the proposed testing procedure is to check for significant coefficient of the log variance from the GJR-GARCH model in the following specification:

$$\ln(\mathrm{h}_t) = \omega + \alpha|z_{t-1}| + \gamma z_{t-1} + \beta \ln(h_{t-1}) + \delta \ln(\widehat{\sigma}_t^2)$$

Where the estimated variance from the EGARCH model is h_t, $\widehat{\sigma}_t^2$ is the estimated variance from the GJR-GARCH model and z_{t-1} is the standardized residuals from the EGARCH model. The Null hypothesis is that; $\delta = 0$, which is in effect testing for significance of the δ in the above equation and non-significance implies $\delta = 0$ and therefore the EGARCH in this case will be the preferred model relative to the GJR-GARCH model.

Rejection percentage of the Null hypothesis of $\delta = 0$ base on Ling and McAleer (2000) test

Test at 5% sig. level	Null Model	Alternative	Local Currency (%)	Dollars (%)
Ling–McAleer	EGARCH	GJR-GARCH	0	0
Ling–McAleer	EGARCH	GARCH	0	33

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