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When the market becomes inefficient: Comparing BRIC markets with markets in the USA☆

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ABSTRACT

A rational investor will believe that an efficient market today will remain efficient tomorrow. However, when emotions take over, markets are no longer efficient. Further, they may remain so for longer anyone can forecast. Evidence of such inefficiencies is prominent in large emerging markets in Brazil, Russia, India and China and also in developed markets in the USA. When a market is inefficient and sentiments play a dominant role in an investor's decision making, valuation by any existing asset pricing model would produce a suboptimal risk–return relationship. Standard pricing technology will guide a rational investor to wrong policies for his new investments or for reallocating his old investments. In an alternative approach, we have worked out a model which incorporates market sentiments in the domain of the standard rational model of asset pricing. Our model is applicable for a 'less than' efficient market and, therefore, may be a useful input in investors' toolkits.

1. Introduction

In 2008–09, when the US economy was passing through the worst phase of its financial recession, some of the emerging markets, particularly markets in BRIC economies became the focus of attention of investors, the financial press and researchers. The term 'BRIC' refers to four countries namely Brazil, Russia, India and China which are larger and faster-growing emerging market economies in the world. Investors throughout the globe are continually discovering new avenues of investments in these markets. According to Goldman Sachs (2010) BRIC markets comprise 18% of the world market capitalization, and that share is steadily growing. Their researchers predicted that by 2030 market capitalization of each of these four emerging markets may exceed that of the USA. It is naturally a challenge for market researchers to develop a model for pricing of securities that could be applicable to these markets.

A natural question that might arise is: Do emerging BRIC markets need special study? The answer is inherent in the unique features of those markets. Before the 1990s, when these economies were relatively autarkic, the business in financial markets was confined to domestic players. Therefore, those markets were not developed enough. But, when these economies started to open up, financial markets grew faster than anyone had forecasted. The resulting effect was twofold: first, price volatility increased considerably and second, markets became hypersensitive to investors' sentiments. Investors in these markets overreact not only to local news but also to news originating in other markets. In particular, news of economic distress in USA since July 2007 spilled over to BRIC markets. Unlike a developed market, countervailing forces are less active in these markets and, therefore, any common information disclosure fuels herd behavior that leads to a significant upturn/or downturn in prices. Stock market crashes in India in May 2004 and May 2006 were the examples. The principal reason for the crash in May 2004 was political turbulence which had a short-term effect on financial markets (see Majumder, 2006). Conversely, the market crash in May 2006 was due to the rise in interest rates in the United States. The effect was a reduction in foreign institutional investments (FII) in the relatively riskier emerging markets. FII withdrew from Indian stock markets and markets crashed. The outcomes of both the incidents were independent of the fundamentals of Indian firms.

Over the last three decades, evidence of market inefficiencies has been widely documented by several scholars. BRIC markets are not exempt. The evidence is that on many occasions equity prices do adjust to new information, but the adjustment process is not instantaneous (see Barberis, Shleifer, & Vishny, 1998; Chopra, Lakonishok, & Ritter, 1992). In such circumstances, strong autocorrelations are induced in equity returns. Positive autocorrelations in the short-run (momentum behavior) and negative autocorrelations in the long-run (mean-reverting behavior) are commonly observed phenomena in developed as well as emerging markets. For developed markets, we can quote Blandon (2007), Jegadeesh and Titman (1993),

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Avramov, Chordia, and Goyal (2006), Pesaran and Timmermann (1995), Kramer (1998) who empirically established the existence of autocorrelation in equity returns for daily, weekly and monthly horizon. Chen, Su, and Huang (2008) observed positive autocorrelation in the US stock markets even in shorter horizon returns than daily returns. Similar results for various emerging markets were documented by many authors. Predictability in stock returns through time in 11 emerging stock markets in the African continent was systematically examined by Appiah-Kusi and Menyah (2003) who discovered inefficiencies in many of these markets. In a similar way, evidence of nonlinear serial dependence in market returns in 10 Asian emerging stock markets was reported by Lim, Brooks, and Hinich (2008). Their research further revealed that the degree of efficiency in these markets changes over time. Serial correlations in market returns in other emerging markets were documented by Chang, Lima, and Tabak (2004), Mollah (2007), Ma (2004), Squalli (2006) and many others. Empirical results by these authors established that in many occasions past returns contain additional information about expected stock returns. In addition to the above, even in a developed market like the USA, it can be observed that equity returns are more volatile than implied by equity fundamentals (e.g. Leroy & Porter, 1981; Shiller, 1981, 1987). The volatility in these returns further increases in periods of high inflation (Lee, Jiang, & Indro, 2002). These characteristics of equity returns are even common in BRIC markets and also the volatility in equity returns in these markets is higher as compared to developed markets (see Parametric Portfolio Associates, 2008). These are common evidence of inefficiencies in emerging as well as developed markets. There is a growing consensus that these inefficiencies have an impact on the macro economy because they could seriously limit the ability of the stock market to allocate funds to the most productive sectors and potentially hamper long-term growth (see Kavussanos & Dockery, 2001; Mookerjee & Yu, 1999).

In this context, it is interesting to examine whether BRIC markets confirm the risk-expected return relationship worked out in well-known asset pricing models of yesteryear. Such models are applicable when equity prices are not driven by any sentiments or stocks are not systematically overvalued or undervalued by market players. In such circumstances, markets act like efficient markets (Fama, 1970, 1991, 1998). However, an anomaly arises when those assumptions do not apply. Particularly for BRIC markets or for other emerging markets or when stock returns are predictable through time, it is imperative to explore the answer to the question: what are the additional factors that determine an investor's expectation of stock returns? Paradoxically, no such factors are identified yet which can be a proxy for investors' sentiments. Therefore, unsurprisingly, common models do not include investors' sentiments and hence valuations by them often lead to mispricing (see Bird, Menzies, Dixon, & Rimmer, 2011). For the purpose of avoiding this mispricing, several scholars advocate an unconventional approach to asset pricing. One of these approaches might be an unconditional or conditional autoregressive processes which are expected to perform better compared to a standard arbitrage pricing model, particularly when stock returns are predictable through time. This might be the motivation of Conrad and Kaul (1988), LeBaron (1992), Koutmos (1997), Shin (2005) and many others to model stock returns as a suitable autoregressive process. However, their models are commonly criticized on two grounds: one, they are based on empirical properties of the data and hence they are sample/situation-specific and two, on some occasions, lagged returns cannot explain a major portion of the variation in equity returns. We can quote from Conrad and Kaul (1988) that variation through time in short-horizon expected returns is 26% of the return variance for the smaller portfolios and 1% for the larger portfolios. Alternatively, the researcher can select a combination of the market return and lagged returns to develop an empirical model providing a better fit to the equity data. However, critics may question the theoretical justifications of these models.

In an equity market where investors' sentiments are prominent, equity returns become predictable, at least partially, by past observations. Conventional asset pricing models cannot explain such predictability in stock returns (Ferson & Korajczyk, 1995). Consequently, it would be misleading to work with these models using input data which have significant predictability. In contrast, we may propose that the domain of the standard rational model for asset pricing may be widened by incorporating collective sentiments of investors. In the line of the methodology adopted by Majumder (2011a), we suggest that equity price changes due to investors' sentiments (collective) can be modeled and isolated from original equity price movements (or returns). The residual part is the portion of the equity price (or return) that is governed by factors which caused a systematic change in it. Therefore, if a hypothetical stock market is constructed using prices (or returns) as that of the residual part, and all other parameters are identical to the original equity market, then such a market must be an efficient market. In that market, investors' sentiments cannot induce investors to systematically overvalue or undervalue a stock and, therefore, apart from the noise, the equity price (or return) is governed only by its fundamental value. It is, therefore, expected that hypothetical market returns are, in general, not serially dependent and so meet the prerequisites of applying a standard asset-pricing model. Any bond or stock pricing model could be well applicable for this market. Our above hypothesis can be justified empirically by exploring following issues for an emerging market: i) are stock returns predictable over time? ii) if so, are hypothetical market returns unpredictable? Empirical investigation in the above line provides a kind of validation of our model. This approach, however, requires a suitable statistical tool which can measure the degree of dependence in asset returns. The ‘Hurst exponent’ as recommended in many recent papers may serve this purpose (Assif, 2012; Davidsson, 2011 and Grech & Mazur, 2004).

In finance literature, the Hurst exponent is often referred to as the “index of dependence” of a time series (Hurst, 1951 and Peters, 1994). This measure allows us to track the evolution of the efficiency through the time or compare the degree of efficiency across markets (Cajueiro & Tabak, 2004a, b; Grech & Mazur, 2004; Lim, Brooks, & Kim, 2008). In this perspective, the traditional focus of absolute market efficiency has been shifted to relative market efficiency referring to multiple periods or more than one market. The magnitude of the Hurst exponent (H) varies in the range 0 to 1. Based on this value a time series can be classified into three categories: (1) $H=0.5$ indicates a random series; (2) $0<H<0.5$ indicates an anti-persistent series and (3) $0.5<H<1$ indicates a persistent series. An anti-persistent series has the characteristic of “mean-reverting”, which means an up value is more likely followed by a down value, and vice versa. The strength of “mean reverting” increases as H approaches 0. A persistent series is trend reinforcing, which means the direction (up or down compared to the last value) of the next value is more likely the same as current value. The strength of the trend increases as H approaches 1. Therefore, if the Hurst exponent departs from 0.5, we may infer the existence of nonlinear serial dependence in asset returns. The magnitude of this measure reflects the degree of efficiency which is compared across BRIC markets and markets in the USA in different time periods. The degree of efficiency in original and hypothetical markets in each country is compared which is prerequisite before manipulating the asset pricing model designed in this paper. Our model will widen the scope of familiar asset pricing models ranging from an efficient to an inefficient market. The rest of the paper is organized as follows: Section 2 explores empirical regularities in BRIC market returns. A comparison of these markets with markets in USA is also included in this section. Section 3 describes the asset pricing model for BRIC markets. Section 4 provides empirical findings. Conclusions are given in Section 5.

2. Empirical regularities in BRIC markets returns: a comparison with the USA

Asset pricing models, confirming relationship between market risks and portfolio returns, have been recognized as useful quantitative tools behind an investor's asset allocation strategies or in monitoring performances of his existing investments. These models are useful to the extent they are supported by empirical regularities observed in market returns. Unfortunately, all conventional forms of these models and their empirical validity have been questioned by several scholars over past 20 years (see Bird et al., 2011; Majumder, 2011a, b). This tenet of research was the exploration of certain regularities in market returns which were not the fruit of the standard models. Predominant among these observed empirical phenomena would be the predictability of portfolio returns through time. On many occasions, past returns contain additional information about expected asset returns which lead asset returns to be serially correlated. Serial dependence in portfolio returns is evidence in favor of market inefficiency which is examined by us for BRIC markets and compared with the USA. This is performed using a statistical tool called 'Hurst exponent' (Hurst, 1951). The methodology for computing the Hurst exponent and the testing procedure are given in Appendix A. Based on the global recession of 2007–09, total sample period (i.e. 1st April, 2001 to 31st March, 2011) is divided into two sub periods, pre-crisis period (1st April, 2001 to 30th June, 2007) and during and post crisis period (1st July, 2007 to 31st March, 2011). The Hurst exponent based on daily portfolio returns on MSCI[1] country indices are computed for these periods.

The Hurst exponent computed for daily market returns in five countries (viz. Brazil, Russia, India, China and USA) for three different time periods[2] are reported in Table 1. The notable divergence in the values of the Hurst exponent above and below 0.5 indicates that select markets were not uniformly efficient for all sample periods in terms of serial dependence in market returns (Table 1). Among BRIC markets, markets in India and China which were relatively efficient in the pre-crisis period i.e. before June 2007, became inefficient after June 2007. Significant Hurst exponents at greater than 0.6 for during and post crisis period for above markets indicate existence of positive serial dependence in market returns. Conversely, Russian markets, which were inefficient in pre-crisis period i.e. before June 2007, remained inefficient after June 2007. However, the nature of serial dependence was opposite for these markets in pre- and post-crisis periods (Table 1). Brazilian markets were inefficient based on full sample period i.e. 1st April, 2001 to 31st March, 2011 and also pre-crisis period i.e. 1st April, 2001 to 30th June, 2007. However, it became relatively efficient after June 2007. This might be the consequence of policies adopted by the Brazilian government during that time.

The Hurst exponent for market returns in USA was relatively closer to 0.5 based on the full sample period, i.e. 1st April, 2001 to 31st March, 2011, confirming market efficiency in US markets. It can, however, be observed that US markets became inefficient after June 2007 which was indicated by the higher value of the Hurst exponent at 0.676 for the period starting from July, 2007. The surge in the value of the Hurst exponent for the above period indicated that the recession had a significant impact on the degree of efficiency in US markets. Because price movements in that period could not be explained fully by economic or political news, but apparently by herding, US markets became more fragile. The resulting effect was higher inefficiency in those markets. Compared to emerging markets in Brazil, India, Russia and China, US markets became increasingly inefficient since July 2007 which was reflected in non-randomness in market returns in those markets. The effect subsequently spilled over to BRIC markets and other emerging markets.

The examples of five countries reveal that market efficiency is often a sample dependent phenomenon. Markets which were recognized as efficient based on a sample period turned out to be inefficient for another period or for any sub period of the total sample period. When markets become inefficient, valuation by any existing asset pricing model would likely produce a suboptimal risk–return relationship. An investor might be misled into adopting inappropriate policies for his new investments or for reallocating his old investments.

3. The asset pricing model for BRIC markets

3.1. Transforming the original market to an efficient market

Any upturn/downturn in equity prices might be the result of any of the thousands of unforeseen events and subsequent sentiments cultivated by them. These events might be an election or a scam or bankruptcy of a large corporate body or many others. These events are not predictable. All the same, influencing market sentiments they change overall supply/demand conditions and consequently disrupt the stability of markets. While it is impossible to predict ex-ante all of these events causing stock price movements, the common approach to develop an asset pricing model accepted by earlier generation economists includes selecting firm-specific, market-specific and macroeconomic factors which have an influence on general decisions making by an investor. Practically, these factors are of two types: one set of factors is correlated with equity fundamentals and the other set of factors is uncorrelated with them. The former set includes implicit market risks, firm size, leverage, earnings-to-price ratios, book-to-market equity ratios, domestic inflation, interest rates etc. These factors cause systematic variation in stock returns. In contrast, nonfundamentals would essentially be market sentiments which make the stock return depart from its fair values. In the course of time, however, it reverts to its original position. Therefore, the short-run expectation of the return of a stock depends, with other factors, on market sentiments. However, in the long run, the market reaches its normal position where the effects of sentiments are zero and, therefore, the expectation would be consistent with fundamentals. Therefore, the return based on the firm's equity prices at time t, R_t^E, can be broadly decomposed into two parts: the part that is consistent with equity fundamentals (R_t^{Ex}), and the part that is unexplained by fundamentals (R_t^{UEx}):

$$R_t^E = R_t^{Ex} + R_t^{UEx}. \tag{1}$$

It can be assumed that R_t^{Ex} is governed by the factor, F_t, which is composed of the linear combination of all factors correlated to fundamentals. Similarly, R_t^{UEx} may be assumed to be governed by market sentiments, S_t, and the noise (e). Market sentiments are unobservable. However we developed an approach to quantify the effects of market sentiments through modeling returns of the market portfolio which is presented in the next section. If the factors, F_t and S_t are linearly related to form R_t^E, we can write:

$$R_t^E = (1-\alpha)F_t + \alpha S_t + e \tag{2}$$

where α is the relative weight to the factor S_t. Any change in the equity price is observable from the market. However, the influence of either F or S on the equity price cannot be separated directly. We can segregate the effect of F and S from the equity price under certain

[1] MSCI stands for Morgan Stanley Capital International Inc.

[2] Full sample period: 1st April, 2001 to 31st March, 2011; pre-crisis period: 1st April, 2001 to 30th June, 2007; during and post crisis period: 1st July, 2007 to 31st March, 2011.

Table 1
Hurst exponent for MSCI market index.

Country	Full sample period (1st April, 2001 to 31st March, 2011)	Pre-crisis period (1st April, 2001 to 30th June, 2007)	During and post crisis period (1st July, 2007 to 31st March, 2011)
Brazil	0.627*	0.681*	0.557
Russia	0.489	0.387*	0.618*
India	0.544	0.506	0.670*
China	0.556	0.520	0.615*
USA	0.522	0.551	0.676*

* The Hurst exponent is significant at 1% level of significance.

reasonable assumptions: factors F and S can be viewed as two assets which form a portfolio E. Consequently, Eq. (2) can be represented in terms of betas:

$$\beta_{E,S} = (1-\alpha)\beta_{F,S} + \alpha\beta_{S,S}. \tag{3}$$

Where $\beta_{I,S} = \frac{\text{Covariance}(I,S)}{\text{Variance}(S)}$ gives the sensitivity of the returns on asset I (I = E/F/S) to asset S. By definition, the factor S_t is uncorrelated to that of F_t. Therefore,

$$\alpha = \beta_{E,S}. \tag{4}$$

The systematic component of the equity return (R_t^{Ex}) would essentially be the part of the return which is consistent with equity fundamentals and so can be explained by an efficient asset pricing model. In the Eq. (2), this part is $(1-\alpha)F_t$. Using Eqs. (2) and (4), R_t^{Ex} can be solved as below:

$$R_t^{Ex} = E\left(R_t^E - \beta_{E,S}S_t\right) \tag{5}$$

where E(.) is the expectation operator. Unlike the traditional approach, R_t^{Ex} is not the simple expectation of the equity return, but is the expectation of the equity return where effects of market sentiments on a particular stock have been eliminated. Eq. (5) reveals that if a hypothetical equity market is formed with the equity return as $R_t^{EH} = (R_t^E - \beta_{E,S}S_t)$ and all other parameters are identical to the existing equity market, then such a market would be close to an efficient market because, in that market, equities are not systematically overvalued or undervalued by market players and returns are consistent with fundamentals. The above market may be used efficiently as an input in any common bond or stock pricing model.

3.2. The market sentiments

It is a stylized fact in developed as well as emerging markets that equity returns are more volatile than implied by equity fundamentals (e.g. Leroy & Porter, 1981; Shiller, 1981, 1987). This additional volatility in equity returns might be due to market sentiments which introduce systematic risks in it (see Lee et al., 2002). Such risks can be described as price risks of a diversified market portfolio when effects of market sentiments are properly summarized into prices of that portfolio (Majumder, 2011a). However, sentiments may not be only factors behind movements in the market price. The market price moves due to the combined effect of market fundamentals and collective investors' sentiments. It is, however, not difficult to segregate the above two effects by fitting a linear model.

Similar to a conventional asset pricing model, we assume that the market portfolio is a well-diversified portfolio which is the optimal portfolio for at least one utility-maximizing investor. Because of the diversified nature of that portfolio, the unsystematic risks of each asset sum to zero. The only risk that exists in the market portfolio is the systematic risk. Therefore, the price/return of such a portfolio is regulated by those factors which fuel systematic risk. These factors may be of two types: one linked to market fundamentals and others not so linked. Factors which are linked to market fundamentals cause permanent variation in market prices. This part of the market price is essentially unpredictable and characterized by a random walk component. Apart from this, it is a commonly observed phenomenon that the market price takes long temporary swings away from fundamental values. The outcome might be a stationary variation in the market price (Fama & French, 1988). This part of the market price is often explained by non-fundamental factors such as investors' sentiments. Therefore, in the line of Fama & French (1988), natural log of the market price (P_t^M) can be written as sum of a random walk (q_t) and a stationary component (z_t),

$$P_t^M = q_t + z_t \tag{6}$$

$$q_t = q_{t-1} + \mu + u_t \tag{7}$$

where μ is the drift and u_t is the white noise. The implied model for the market return,

$$\begin{aligned} R_t^M &= p_t^M - p_{t-1}^M \\ &= (q_t - q_{t-1}) + (z_t - z_{t-1}) = \mu + u_t + (z_t - z_{t-1}). \end{aligned} \tag{8}$$

Because z_t is stationary, so is $(z_t - z_{t-1})$ which we denote S_t. Therefore,

$$R_t^M = \mu + u_t + S_t. \tag{9}$$

Eq. (9) reveals that the market return is the sum of white noise process (first differenced random walk) (u_t), a stationary process (S_t) and a constant drift (μ). S_t may be specified by an AR(m) process:

$$S_t = \sum_{i=1}^{m} \varphi_i S_{t-i} + \varepsilon_t \tag{10}$$

where φ_i is the coefficient associated with S_{t-i} and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. The part u_t in Eq. (9) can be interpreted as the return in an efficient market and S_t is the distortion of the market return caused by market sentiments. In other words, S_t can be described as the stationary departure of the market return from its fair value (Majumder, 2011a). This part of the market return is explained by the exuberance or pessimism by investors to certain information. Consequently, any autocorrelation that is observed in the market return is the result of possible bullish/bearish responses by investors to market information. The model specified in Eqs. (9) and (10) can be estimated by the recursive algorithm used in Kalman Filter technique (see Chui & Chen, 2009).

3.3. The long run versus short run expectations

Let us assume that $\psi(F_1, F_2, --, F_N)$ is a general asset pricing model for a common bond or stock where $(F_1, F_2, --, F_N)$ is the set of factors influencing the value of the underlying asset. Common factors are market returns, interest rates, exchange rates, oil price inflation etc. In the present model, ψ is applied on the transformed returns comprising the hypothetical market. The model isolates the long run expectation of the asset return (E^L) from the short run expectation (E^S). In the long run, the effects of the market sentiments are zero; therefore, the expectation of the asset return would essentially be:

$$E^L\left(R_t^E\right) = E\left(R_t^{EH}\right) = \psi(F_1, F_2, ----, F_N). \tag{11}$$

On the other hand, in the short run, the expectation of the return would be governed by, with other factors, market sentiments and may be assessed from the following equation:

$$E^S\left(R_t^E\right) = E\left(R_t^{EH}\right) + \beta_{E,,S}E(S_t) = \psi(F_1, F_2, ----, F_N) + \beta_{E,,S}\sum_{i=1}^{m}\varphi_i S_{t-i}. \tag{12}$$

If the underlying market is efficient, then equity prices instantaneously adjust to new information. In such a case, unenthusiastic or overenthusiastic responses to information, if any, would occur randomly. Consequently, the long-run and the short-run expectations of the equity return would be identical and, therefore, our model would be transformed to a common asset pricing model.

3.4. The adjustments, when factors F and S are not uncorrelated

Normally, market sentiments are generated as a consequence of firm-specific or macroeconomic news/information released in the market. Consequently, the equity price moves which is the result of combined effects of the news, and sentiments generated by it. Therefore, it can be argued that the factor F, which is consistent with equity fundamentals, might be correlated to investors' sentiments (S). In such a situation, $\beta_{F,S}$ in Eq. (3) would be nonzero. We can estimate $\beta_{F,S}$ by an iterative procedure described below. Eq. (3) gives an estimate of α in terms of betas:

$$\alpha = \frac{\beta_{E,S} - \beta_{F,S}}{1 - \beta_{F,S}}. \tag{13}$$

Using the value of α, the return on the asset F can be evaluated from Eq. (2) as below:

$$F_t = E\left(\frac{\left(1-\beta_{F,S}\right)R_t^E - \left(\beta_{E,S} - \beta_{F,S}\right)S_t}{\left(1 - \beta_{E,S}\right)}\right). \tag{14}$$

Let us denote the value of F_t and $\beta_{F,S}$ in the (i–1)th iteration is $F_t(i-1)$ and $\beta_{F,S}(i-1)$ respectively. Based on Eq. (14), we can compute the ith approximation of F_t as follows:

$$F_t(i) = \frac{\left(1-\beta_{F,S}(i-1)\right)R_t^E - \left(\beta_{E,S} - \beta_{F,S}(i-1)\right)S_t}{\left(1 - \beta_{E,S}\right)}. \tag{15}$$

Using the above equation, the set of values of $F_t(i)$ can be calculated for $t = 1,2,\ldots,n$. Accordingly, the ith approximation of $\beta_{F,S}$ would be,

$$\beta_{F,S}(i) = \frac{\text{Covariance}(F(i), S)}{\text{Variance}(S)}. \tag{16}$$

The first approximation of $\beta_{F,S}$ might be $\beta_{F,S}(1) = 0$. Using Eqs. (15) and (16) it is possible to generate a series of approximations for $\beta_{F,S}$. The process converges if $|\beta_{F,S}(i) - \beta_{F,S}(i-1)| < \varepsilon$. Accordingly, we can obtain a desired degree of accuracy by considering a smaller ε.

4. Empirical findings

Prior to manipulating any asset pricing model for predicting equity returns, it is necessary to examine whether the capital market is informationally efficient. One effective way to test this might be through investigating the serial correlation properties of equity returns. Such a test is also useful to examine existence of investors' sentiments in the equity market. Our sample consists daily closing prices for 74 MSCI industrial/sectoral indices from 5 countries for the period from April 1, 2001 to March 31, 2011. MSCI industrial indices are used to characterize the overall performance of each market. These indices are computed on a free float-adjusted market capitalization weighted methodology which is a popular approach. They are comparable across countries and, therefore, used extensively in empirical research. The Hurst exponent on daily index returns is computed separately for original markets and hypothetical markets where hypothetical market returns are estimated using a two stage algorithm. First, we use a Kalman filter to estimate the time series of the unobservable state variable, S_t, and its dynamics, from data on market returns from 5 different sets of markets and, second, we extend the state-space model to estimate dynamically $\beta_{E,S}$ and R_t^{EH} for select portfolios from each of these markets (all variables are defined in Section 3). Our estimation procedure allows time-varying specifications of all beta variables.

For assessing relative efficiencies in 4 BRIC markets and comparing with USA, Hurst exponents are computed for 12 industrial/sectoral indices for Brazil, 9 indices for Russia, 16 indices for India, 16 indices for China and 21 indices for the USA for three different sample periods (Tables 2 and 3). The sample periods include a) full sample i.e. 1st April, 2001 to 31st March, 2011 b) Pre-Crisis Period: 1st April, 2001 to 30th June, 2007 and c) During and Post Crisis Period: 1st July, 2007 to 31st March, 2011. Test of significance of the Hurst exponent is carried out based on the methodology described in Appendix A. *In the case of Brazil*, overall 36 Hurst exponents are computed for industrial indices separately for original markets and hypothetical markets, of which 19 estimates are significant for original markets and 9 estimates are significant hypothetical markets. The results indicate that original market returns are serially correlated in greater number of occasions compared to returns in hypothetical markets. Similar results can be observed for Russia, India and China. *For Russia*, overall 27 Hurst exponents are computed for industrial/sectoral indices in each market, of which 12 and 4 estimates are significant for original markets and hypothetical markets respectively. *For India*, out of 48 Hurst exponents computed for each markets, 20 estimates are significant for original markets and 10 estimates are significant for hypothetical markets. *For China*, out of 48 Hurst exponents computed for each markets, 20 estimates are significant for original markets and the same figure for hypothetical markets is 10. Therefore, evidence of serial correlations is greater by twofold or more in select industrial indexes in original markets compared to hypothetical markets in each of the above four BRIC countries. Therefore, hypothetical market returns are random walk with limited exceptions, whereas original market returns are not. Deviations from random walk in industry-specific returns in hypothetical markets are few in number. The explanation might be idiosyncratic risks associated with those returns. It can, therefore, be inferred that the transformation proposed by us shifts the original market to a hypothetical market which is closer to an efficient market. The market in the USA, however, might be an exception.

Results provided in Tables 2 and 3 indicate that global recession of 2007–09 adversely affected the efficiency of markets in the USA as well as BRIC markets. Markets in the USA were the worst hit by the recession in terms of market efficiency, followed by markets in India, China, and Russia. The effect of this recession was minimum in the case of Brazilian markets. It is not surprising that due to chaotic financial environments since July 2007, investors overreacted not

Table 2
Hurst exponents for industry/sector specific returns for Brazil, Russia and India.

	The original market			The hypothetical market		
	Full sample	Pre-crisis	During and post crisis	Full sample	Pre-crisis	During and post crisis
Brazil						
Banks	0.602*	0.664*	0.481	0.508	0.578	0.419
Energy	0.601*	0.628*	0.591*	0.470	0.465	0.572
Oil and gas	0.602*	0.628*	0.591*	0.471	0.460	0.572
Telecom	0.517	0.583*	0.508	0.425	0.477	0.454
Paper and forest product	0.587*	0.453	0.683*	0.684*	0.564	0.838*
Capital goods	0.506	0.513	0.608*	0.505	0.472	0.615*
Food and staples retail	0.464	0.536	0.463	0.459	0.495	0.421
Utilities	0.581*	0.620*	0.498	0.265*	0.333*	0.526
Financials	0.607*	0.664*	0.502	0.532	0.589*	0.422*
Beverages	0.577	0.618*	0.523	0.546	0.517	0.635*
Large cap	0.625*	0.675*	0.556	0.583	0.534	0.701*
Mid cap	0.530	0.575	0.562	0.578	0.510	0.635*
Russia						
Banks	0.781*	0.483	0.649*	0.591	0.519	0.533
Energy	0.491	0.397*	0.588*	0.514	0.434	0.570
Metals and mining	0.490	0.426	0.684*	0.517	0.472	0.592*
Oil and gas	0.489	0.397*	0.587*	0.514	0.434	0.571
Telecom	0.479	0.525	0.555	0.460	0.518	0.535
Utilities	0.530	0.556	0.556	0.531	0.548	0.570
Large cap	0.486	0.427	0.620*	0.504	0.444	0.586
Mid cap	0.610*	0.454	0.656*	0.613*	0.473	0.619*
Small cap	0.653*	0.537	0.815*	0.618*	0.557	0.570
India						
Banks	0.524	0.479	0.647*	0.438	0.505	0.473
Energy	0.504	0.447	0.628*	0.421	0.421	0.563
Capital goods	0.611*	0.611*	0.681*	0.501	0.508	0.329*
Financial	0.572	0.508	0.664*	0.458	0.478	0.515
Pharmaceuticals	0.515	0.506	0.667*	0.537	0.599	0.492*
Information technology	0.486	0.442	0.654*	0.575	0.641*	0.473
Metals and mining	0.479	0.501	0.646*	0.354*	0.466	0.499
Telecom services	0.471	0.471	0.563	0.488	0.481	0.649*
Automobiles	0.558	0.548	0.632*	0.598*	0.531	0.531
Automobile components	0.562	0.550	0.635*	0.609*	0.537	0.535
Utilities	0.503	0.509	0.639*	0.500	0.402*	0.531
Construction and engineering	0.627*	0.581*	0.693*	0.547	0.543	0.453
Electrical equipment	0.589*	0.546	0.618*	0.506	0.438	0.423
Large cap	0.521	0.440	0.671*	0.516	0.543	0.493
Mid cap	0.543	0.480	0.700*	0.400*	0.362*	0.421
Small cap	0.534	0.459	0.760*	0.421	0.460	0.540

Note: Full sample: 1st April, 2001 to 31st March, 2011; Pre-crisis: 1st April, 2001 to 30th June, 2007; During and post crisis: 1st July, 2007 to 31st March, 2011.
* The Hurst exponent is significant at 1% level of significance.

only to local news, but also to news originating in the other markets, especially when the news was adverse. In particular, news of economic distress in the USA, viz. bank and corporate fragility, put additional pressure on BRIC markets as well. This may have caused the dramatic surge in volatility in these markets after June 2007 (Table 4). During the pre- and post-crisis periods, all four BRIC markets acted almost in a similar fashion in respect of market efficiency. The behavior of the US markets, however, was not fully comparable. The US markets which were efficient in the pre-crisis period became inefficient afterwards. It is noteworthy that inefficiencies which were introduced in industry-specific returns in the US markets during and post crisis could not be rectified fully through the transformation proposed in this paper (Table 3). Such inefficiencies could possibly be the result of firm-specific or industry-specific risks which caused an unsystematic variation in stock prices in the USA during that period. We should observe that the scope of our model is limited in incorporating systematic risks caused by market sentiments.

Volatilities in returns, measured in terms of standard deviation of daily returns, averaged over select industries in 5 countries in each of the original market and the hypothetical market is reported in Table 4. There are notable differences in volatilities in these markets: volatilities in the hypothetical market are lower for all select periods compared to the original market. It is worthwhile to restate the fact that higher volatilities in equity returns might be the effect of investors' sentiments. This effect is lower in the hypothetical market.

5. Conclusion

The efficient market hypotheses and its validity for emerging markets were a fertile topic of debate in Finance. However, the dilemma of market efficiency still remains intractable. Any literature review on the subject may identify voluminous number of papers whose conclusions are conflicting. Such an overview should, however, come as no surprise due to the fact that efficiency of financial markets is often a sample- or situation-dependent phenomenon. Our empirical analysis for BRIC markets and comparisons with markets in the USA reveal that markets which are recognized as efficient based on a sample period turn out to be inefficient for another period or for any sub period of the total sample period. These findings would make it difficult to segregate of an “efficient” set of markets from “inefficient” counterparts. Simultaneously, it becomes more difficult the choice of an asset pricing model which is applicable for sets of markets. The foundation of inefficiency in these markets is well encapsulated by the words irrational exuberance or pessimism which reflects a period when emotions take over and valuation plays, at

Table 3
Hurst exponents for industry/sector specific returns for China and the USA.

	The original market			The hypothetical market		
	Full sample	Pre-crisis	During and post crisis	Full sample	Pre-crisis	During and post crisis
China						
Airlines	0.548	0.436	0.655*	0.490	0.425	0.599*
Energy	0.545	0.491	0.592*	0.521	0.479	0.539
Information technology	0.489	0.418*	0.671*	0.445	0.421	0.678*
Metals and mining	0.564	0.474	0.706*	0.541	0.466	0.684*
Real estate	0.631*	0.597*	0.636*	0.643*	0.579	0.579
Telecom	0.612*	0.552	0.535	0.506	0.442	0.447
Chemicals	0.449	0.469	0.449	0.429	0.486	0.502
Capital goods	0.519	0.414	0.639*	0.478	0.401*	0.591*
Automobiles	0.530	0.523	0.605*	0.529	0.544	0.559
Oil and gas	0.544	0.491	0.591*	0.478	0.479	0.539
Auto components	0.530	0.523	0.605*	0.529	0.544	0.559
Computer peripherals	0.476	0.412	0.665*	0.423	0.409*	0.570
Consumer durable	0.427	0.478	0.585*	0.474	0.523	0.598*
Large cap	0.593	0.573	0.596*	0.599*	0.547	0.554
Mid cap	0.467	0.420*	0.695*	0.436	0.428	0.548
Small cap	0.581*	0.501	0.779*	0.536	0.484	0.741*
USA						
Airlines	0.486	0.439	0.651*	0.426	0.400*	0.533
Banks	0.612*	0.468	0.600*	0.573	0.491	0.579
Energy	0.485	0.526	0.513	0.550	0.530	0.515
Automobiles	0.578	0.534	0.726*	0.605*	0.583*	0.747*
Information technology	0.516	0.559	0.603*	0.507	0.544	0.634*
Chemicals	0.461	0.632*	0.632*	0.485	0.387*	0.659*
Financials	0.581*	0.500	0.626*	0.591*	0.661*	0.559
Auto components	0.516	0.475	0.665*	0.532	0.501	0.698*
Pharmaceuticals	0.478	0.549	0.559	0.473	0.526	0.535
Real estate	0.513	0.501	0.509	0.508	0.468	0.490
Retailing	0.511	0.471	0.659*	0.555	0.510	0.663*
Telecom	0.666*	0.690*	0.532	0.613	0.619	0.491
Utilities	0.693*	0.730*	0.643*	0.733*	0.736*	0.673*
Insurance	0.569	0.488	0.664*	0.599*	0.513	0.650*
Capital goods	0.552	0.556	0.687*	0.585	0.557	0.570
Paper and forest product	0.596	0.495	0.637*	0.615*	0.496	0.631*
Healthcare	0.529	0.591*	0.562	0.520	0.566	0.529
Consumer staples	0.511	0.564	0.664*	0.519	0.558	0.642*
Large cap	0.511	0.539	0.636*	0.531	0.541	0.529
Mid cap	0.523	0.552	0.627*	0.534	0.541	0.642*
Small cap	0.502	0.513	0.626*	0.527	0.541	0.615*

Note: Full sample: 1st April, 2001 to 31st March, 2011; Pre-crisis: 1st April, 2001 to 30th June, 2007; During and post crisis: 1st July, 2007 to 31st March, 2011.
* The Hurst exponent is significant at 1% level of significance.

best, a limited role in determining equity prices. An investor might be misled into adopting inappropriate policies for his new investments or for reallocating his old investments. Erroneous investment strategies, collectively, will affect the real economy by disrupting the optimal allocation of resources. The question is 'what would be the appropriate asset pricing model for those markets which are not uniformly efficient for all periods?'. The model proposed by us might be an answer. It provides a direction of incorporating market sentiments in the domain of the familiar model of asset pricing. The process of transforming the original market to a hypothetical market, which is relatively efficient, smooths out, at least partially, the abnormal volatility and large autocorrelations often found in the asset return data without changing the properties of the original asset pricing model. The outcome might be a superior alternative to a conventional model in terms of its greater applicability. Our empirical study using select industry-wise data for BRIC markets and markets in the USA established the following: often, original equity market returns are serially correlated reflected in the notable divergence in

Table 4
Average volatility in returns.

Country	Number of industries/sectors	Average volatility in the original market			Average volatility in the hypothetical market		
		Full sample	Pre-crisis	During and post crisis	Full sample	Pre-crisis	During and post crisis
Brazil	12	2.585	2.308	2.970	1.183	1.166	1.204
Russia	9	2.593	2.099	3.245	2.477	1.949	3.161
India	16	2.205	1.871	2.653	1.274	1.233	1.321
China	16	2.279	1.969	2.700	1.673	1.604	1.765
USA	21	1.770	1.304	2.313	1.132	0.937	1.378

Note 1: Average is taken over select industries/sectors of each country.
2: The volatility is measured in terms of standard deviation of daily returns.

the values of the Hurst exponent above and below 0.5. Conversely, in the majority of cases, the Hurst exponent for hypothetical market returns is insignificant indicating weak serial dependence/ or independence in those returns. Therefore, transformed returns comprising the hypothetical market are, in general, not serially dependent and so meet the prerequisites of applying a standard asset-pricing model. Any conventional bond or stock pricing model could, therefore, be efficiently manipulated for those returns. The approach will widen the scope of asset-pricing models ranging from a strict efficient market to an inefficient market.

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Appendix A. Rescaled range analysis for computing the Hurst exponent

The Hurst exponent (H) is the classical test to detect long memory in time series. To compute H, Mandelbrot (1972) suggested the use of the 'rescaled range' statistic (R/S), originally developed by Hurst (1951). The rescaled range statistic is defined as:

$$\left(\frac{R}{S}\right)_n = \frac{1}{s_n}\left[\underset{1<K<n}{\text{Max}}\sum_{j=1}^{K}\left(X_j-\bar{X}_n\right) - \underset{1<K<n}{\text{Min}}\sum_{j=1}^{K}\left(X_j-\bar{X}_n\right)\right]$$

for $1<k<n$, where $\bar{X}_n$ is the sample mean and s_n is the usual estimator for standard deviation:

$$s_n = \left[\frac{1}{n}\sum_{j=1}^{n}\left(X_j-\bar{X}_n\right)^2\right]^{\frac{1}{2}}.$$

The first term in $\left(\frac{R}{S}\right)_n$ is the maximum (over k) of the partial sums of the first k deviations of X_j from the sample mean. The second term is the minimum (over k) of this same sequence of partial sums. Therefore, the difference between the two quantities, called the 'range', is always nonnegative and hence $\left(\frac{R}{S}\right)_n$. The R/S statistic asymptotically follows the relation $\left(\frac{R}{S}\right)_n \approx C.n^H$ where C is a constant. Therefore, the value of H can be obtained by running a simple linear regression over a sample of increasing time horizons:

$$\log\left(\frac{R}{S}\right)_n = \log(c) + H * \log(n).$$

When the series is a Brownian motion, H has to be 0.5, when it is persistent H will be greater than 0.5, and when it is anti-persistent H will be less than 0.5.

Although it has long been established that the rescaled range statistic $\left(\frac{R}{S}\right)_n$ has the ability to detect long-range dependence, Lo (1991) argued that this statistic may be significantly biased because it is unable to distinguish between short term and long term dependence and called it a "severe shortcoming in the applications of the R/S analysis". However, the method for estimating such bias was first proposed by Anis and Lloyd (1976) and subsequently revised by Peters (1994). Their method was based on computing expected values of Hurst exponent. The expected value of rescaled range $\left(E\left(\frac{R}{S}\right)_n\right)$ as proposed by Peters (1994) may work as a reference series for generating the expected Hurst exponent. In the line of Peters (1994), Weron (2002) and Sanchez Granero, Trinidad Segovia, and Garcia Perez (2008) proposed following formula for estimating $\left(E\left(\frac{R}{S}\right)_n\right)$:

$$E\left(\frac{R}{S}\right)_n = \left(\frac{n-0.5}{n}\right) * \frac{\Gamma\left(\frac{n-1}{2}\right)}{\sqrt{\pi}\Gamma\left(\frac{n}{2}\right)} * \sum_{r=1}^{n-1}\sqrt{(n-r)/r} \quad \text{if} \quad n \le 340$$
$$\left(\frac{n-0.5}{n}\right) * \sqrt{\frac{2}{n * \pi}} * \sum_{r=1}^{n-1}\sqrt{(n-r)/r} \quad \text{if} \quad n \ge 340.$$

The expected Hurst exponent (E(H)) is the slope coefficient that results from the regression of $E\left(\log\left(\frac{R}{S}\right)_n\right)$ on log(n). The variance of the Hurst exponent is given by

$$\mathrm{Var}(H)_n = \frac{1}{N}$$

where N is the sample size. We may use following t-test statistics for testing significance of estimated H (see Peters, 1994):

$$t = \frac{H-E(H)}{\sqrt{\frac{1}{N}}}.$$

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