INTERNATIONAL REAL ESTATE REVIEW

2012 Vol. 15 No. 3: pp. 283 - 305

Return Persistence in the Indian Real Estate Market

Sanjay Rajagopal^{*}

DBA, Associate Professor of Finance, Western Carolina University; 1 University Drive, 122B Forsyth Building, Western Carolina University, Cullowhee, NC 28723; Phone: 828-227-3158; Email: <u>rajagopal@email.wcu.edu</u>

Patrick Hays

PhD, Professor Emeritus, Western Carolina University

Over the last decade, numerous factors including robust economic growth, population pressure, and the mounting need for office space among growth sectors such as information technology have placed significant upward pressure on Indian realty prices. The easing of government restrictions on foreign investments and venture capital into Indian real estate have provided an additional fillip to the real estate market in the country, and the confluence of such factors appears to have contributed to a speculative bubble in Indian real estate equities in the latter part of the decade. By using this bubble period as a case study, we test for the existence of long memory among real estate equities. For the January 2006-December 2008 period, we employ three self-affine fractal analysis techniques (classical rescaled range, roughness-length, and the variogram/structure function methods) to estimate the Hurst exponent, and find significant evidence of long memory in the Bombay Stock Exchange (BSE) Realty Index. Return persistence is further confirmed by the more powerful Lo's modified rescaled range analysis (MRSA), which is robust to short-term dependence. In addition to potential regulatory policy implications for this emerging market, our results have ramifications for modeling and forecasting returns, as well as for technical trading rules.

Keywords

Fractal analysis; Long-Memory; Return persistence; Market efficiency; Indian Real Estate; Real Estate bubbles

^{*} Corresponding Author

1. Introduction

The last decade has seen significant progress in the evolution of the Indian real estate market. Robust economic growth – spurred by sectors such as information technology (IT) and information technology enabled services (ITeS) – and a large urban population with higher incomes have placed considerable pressure on the price for residential and commercial real estate. Furthermore, between 2001 and 2005, India eased the regulation of foreign investment into the country's real estate sector, which augmented the underlying economic demand for realty, and added to the pool of liquidity chasing avenues for property investment. The more recent introduction of real estate investment trusts (REITs) represents just another step in the transition of Indian real estate financing from a regime of almost exclusive dependence on pre-construction sales and bank loans to one of institutional and retail funding by both domestic and foreign entities (Agarwal & Dahiya, 2007).

The fundamental demand drivers and foreign investment policy initiatives of the Indian government appear to have contributed to a euphoria among property investors that sent real estate equities soaring in the latter part of the last decade, and prompted some to dub these stocks as "India's New Tech" (Anand, 2009). Indeed, it appears that a confluence of such factors contributed to a speculative bubble in Indian real estate during the more recent years. We get some indication of the froth in this market when we consider that in March 2005, the U.S. hedge fund Farallon Capital Management purchased an 11-acre tract in Mumbai for \$54.5 million per acre, a purchase which local developers reportedly called "an act of idiocy". Yet, their bid of \$95.5 million per acre for a proximate property a few months later was reportedly the second-lowest submitted for the tract (Pitalwalla, 2006). On the financial side, in the 2006-2008 period, average real estate equity prices sharply rose from their norm, and from the pattern of the broader market indices which themselves experienced an upward run during the middle of the decade. This is suggested by the behavior of the Bombay Stock Exchange (BSE) Realty Index, which sharply deviated from its norm over the Jan 2006-Dec 2008 period. The graph below compares the movement of the realty index with the most widely followed broader index for the Indian market, the Sensex.

The relative behavior of the two indices over the period 2006-2008 indicates that the country's real estate equities experienced a surge in value of a significantly greater order of magnitude than that for equities in general. This surge was followed by an offsetting decline in valuations, which exhibited a classic pattern of the creation and implosion of a "bubble". Between January 2006 and January 2008, the BSE Sensex index rose 16.19%. In contrast, the BSE Realty Index rose 989%, over the same period. A precipitous decline then ensued, and both indices approximately reverted to their 2006 levels by the start of 2009. As of February 3, 2009, for example, the Sensex and BSE

Realty indices were 2.5% below and 4.9% above their January 2, 2006 values, respectively.





By using this bubble as a case study, we test whether there was a measurable long memory effect in Indian real estate equities during the period January 2006-December The study is motivated by the following 2008. considerations. First, while several studies have investigated the efficiency of Indian capital markets following the country's experiment with liberalization in the 1990s (e.g. Poshakwale, 2002; Sarkar & Mukhopadhyay, 2005; Chander et al., 2008), the study of the subject remains in its nascent stages. Although the weight of the evidence argues against an efficient market, not all studies are in agreement. Furthermore, none of the existing market efficiency studies have specifically considered the pricing of Indian real estate equities. The issue of efficient pricing in the real estate sector is of special interest in this context since there is some question as to the transparency in this sector which suffers from weak accounting guidelines, suspect accounting practices, and inadequate disclosure (Anand 2009; Range & Choudhury 2009).

A second motivation for our study is the suggestion by some researchers of capital markets that returns trend in a direction due to "market sentiment" or "bias" until an exogenous event changes the bias (see, for example, Peters, 1994). The recent behavior of Indian real estate equities presents a natural experiment for the study of such a hypothesis. When returns are apparently buoyed by investor exuberance or "bias", there may be a measurable long

memory effect as investors use past return information to form expectations about present and future returns. Again, this behavior may be exacerbated by a lack of information due to inadequate transparency among Indian realty companies. In addition to contributing to the literature on the behavior of Indian stock returns by specifically focusing on real estate equities, our study augments the existing corpus of work on long-term memory in financial times series. The study has important practical implications. For example, the presence of long memory in real estate equities would imply that there are at least periodic inefficiencies in the Indian financial markets when technical trading rules can afford the investor superior risk-adjusted returns.

The remainder of the paper is organized as follows. The section below provides an overview of the fundamental demand drivers and regulatory changes that have transformed the Indian real estate landscape over a very brief period. Here, we note the significant rise in foreign direct investment (FDI) into the Indian realty sector in recent years, which may have contributed to a bubble. We then briefly survey the literature on the Indian real estate market, Indian capital market efficiency, and long-term memory. The next section discusses the data employed by the study, and describes the three selfaffine fractal analysis techniques used to estimate the Hurst exponent for detecting long memory. The section also presents and discusses the results of the three fractal analysis techniques for the BSE Realty Index. Following this, we describe the methodology that underlies Lo's modified rescaled range analysis (MRSA) and present the results of this technique for the BSE Realty Index. We conclude the paper with a summary and implications of our study.

2. Economic and Regulatory Factors and the Real Estate Bubble

2.1 Demand Drivers

India is the second-most populous country in the world, with a count of just under 1.03 billion people according to the 2001 census. This number represented a 13.75% total growth over the decade preceding the census, or an annual compound growth of $1.3\%^{1}$. Of this population, 28% resided in urban areas, and the proportion is projected to rise to 40% by 2020. It is expected that this growth will be focused around 60 to 70 large cities with population well in excess of 1 million each² Even though poverty among Indians does remain a challenge, the country has enjoyed strong economic growth following the introduction of economic and financial sector reforms in the early 1990s. The growth in real GDP averaged 7.2% between 2000 and 2008,

¹ www.censusindia.gov.in

² India Vision 2020, Planning Commission, Government of India, December 2002

and was roughly 9.4% between 2005 and 2008.³ Per capita income doubled over the two decades ending 2002, and should a GDP growth of 9% per annum be sustained, we will witness a quadrupling of per-capita income by 2020.⁴ In the interim, projections anticipate real personal disposable income to rise at a rate of 8 to 10% annually in the 2006-2010 period (Jones Lang LaSalle, 2006).

To quote a manager of the New Jersey hedge fund, New Vernon Advisory, "India is one of the last few countries where there is primary demand for real estate rather than individuals trading up".⁵ A large middle class has emerged with this economic growth, estimated in 2006 to be approximately 120 million (Jones Lang LaSalle, 2006). Some analysts expect this middle class to number 583 million by the year 2025 (Beinhocker et al., 2007). The large urban population with increasing purchasing power has placed, and will continue to place, a large demand pressure on residential real estate. Already, it is estimated that urban housing suffers a shortfall of more than 20 million units (Kilbinger, 2007). In addition to the demand for residential real estate, which has stimulated the development of entire residential townships, the emerging urban middle class has spurred the demand for retail space, leading to a boom in the construction of shopping malls and retail hypermarkets (Chaze, 2007). India's middle class also represents a very large pool of skilled labor, with significant academic and vocational qualifications and proficiency in English. Skill, proficiency in English, and low cost are the chief features of India's labor force that has attracted Western companies to outsource business activities to this country, particularly into the IT and ITeS sectors (Naidu et al., 2005). Indeed, over half of the Fortune 500 companies have outsourced the development of software to India (Jones Lang LaSalle, 2003), and the IT and ITeS sectors have been growing at a rate in excess of 30% annually (Jones Lang LaSalle, 2006). Consequently, the country has witnessed an increasing demand for office and residential space in urban areas, especially in the larger cities of New Delhi, Mumbai, Chennai, and Bangalore.

It is not surprising, therefore, that by 2006, the real estate market in India was experiencing a "bull run", with property prices having risen by a reported 150 to 200% over a three and a half-year period (Bamzai, 2006). Anecdotal reports suggest pockets of yet more rapid increase in real estate values, with some residential property prices in Bangalore increasing from \$350 to \$1,975 per square meter in the space of three years (Vogel, 2007). In Mumbai and New Delhi, Grade A commercial properties saw a rise in rental prices of over 100% over a year and a half, ending May 2007 (Roy, 2007). A portion of this increase in real estate values may have been driven by equity redemptions following the bullish period for the stock market which started May 2003 (Bamzai, 2006).

³ Reserve Bank of India Annual Report, August 2009

⁴ India Vision 2020, op cit.

⁵ Rajiv Sahney, quoted in Pitalwalla (2006), p. 14.

2.2 Liberalization of Foreign Direct Investment

Arguably, an important factor that contributes to the run-up in realty prices was the easing of limits in March 2005 on FDI into Indian commercial and residential real estate (Vogel, 2007). India's policy towards institutional investment in property had begun to be liberalized in May 2001, but very stringent threshold requirements in terms of minimum development area, capitalization of developer, and lock-in periods were in place. FDI into real estate was limited to the development of industrial parks, integrated townships, technology parks, and special economic zones (SEZs). According to Press Note No. 2 in the 2005 series issued by the Government of India's Department of Industrial Policy and Promotion (DIPP), 100% FDI was now allowable into built-up infrastructure and construction development projects, subject to certain qualifications. Investment could cover projects such as city and regional-level infrastructures, hospitals, housing, townships, commercial premises, educational institutions, recreational facilities, hotels, and resorts, among others. Qualifications for construction-development projects that pertain to the minimum area to be developed, minimum capitalization of the investing entity, lock-in period for foreign investment prior to repatriation, the speed of development, and restrictions on sale of undeveloped land were still in place, albeit at less stringent levels.⁶ Proposals for qualifying investments would no longer have to receive clearance from the Foreign Investment Promotion Board (FIPB).

This initiative on the part of the Indian government was seen as constituting a significant deregulation of foreign investment into the real estate market, which would boost international equity flow into the property sector (Jones Lang LaSalle, 2005). In 2007, analysts at Jones Lang LaSalle estimated shares of 16% and 26% for real estate in total FDI for the years 2006 and 2007, sharply up from below an estimated 5% share in 2003-2004. This rise in FDI was driven by listed and privately owned real estate companies and institutional investors, and the role of the property sector in attracting foreign capital flows was considered to be "pivotal" (Roy, 2007).

2.3 Ruling on Venture Capital Funds

The liberalization of FDI was preceded by a ruling in 2004 in which the watchdog of the Indian capital markets, the Securities and Exchange Board of India (SEBI), permitted venture capital funds and foreign venture capital investors to invest in companies engaged in real estate. This relaxing of capital market norms was likely important in injecting liquidity into the property sector and improving the real estate investment climate in the

⁶ See Press Note 2, March 2005, Department of Industrial Policy and Promotion, www.dipp.nic.in

country⁷. In its 2006 report on the future of real estate investment in India, Jones Lang LaSalle (2006) notes the rise of real estate funds, observing that they are "increasingly becoming the preferred entry route for cross-border investors, particularly amongst U.S. opportunistic investors". Mainly via joint venture real estate funds, investors such as Citibank, GE Capital, Morgan Stanley, Tishman Speyer, and Warburg Pincus were now active in the Indian property investment market. This advent of real estate funds represented the birth of an additional structure for property investment in India.

In addition to foreign investors, domestic developers, such as Akruti, DLF, Omaxe, Parsvnath, and Sobha, began tapping the buoyant stock market. Public sector and private banks too increased their exposure to the residential and commercial property sectors, increasing their real estate lending by 102% and 52.5%, respectively (Vogel, 2007). In 2006, the possibility of an asset bubble in the realty sector was at least being debated among economists, and the unease of the country's central bank, the Reserve Bank of India (RBI), in this respect led it to nudge up the risk weights on real estate loans made by banks (Pitalwalla, 2006). In 2007, the RBI also disallowed real estate firms from using external commercial borrowing (ECB) to develop integrated townships, a source of financing that had been permitted since 2005 (Agarwal & Dahiya, 2007). Merrill Lynch was making sanguine predictions about the property sector growing at approximately 25% per year, from \$12 billion in 2005 to \$90 billion in 2015. At the same time, bankers warned of a real estate bubble, especially in Mumbai and Bangalore (Wilson, 2006).

2.4 The Real Estate Downturn

By the start of 2008, the subprime mortgage crisis in the U.S. had turned the global investment climate much more cautious, and the Indian property market reflected this loss of appetite for risk. Banks now viewed the country's real estate market as overvalued, and accordingly curtailed their lending. Real estate companies began to encounter increasing difficulty in accessing credit, as capital exited the country "at an alarming rate"; data from the SEBI indicated that foreign institutional investors offloaded net holdings of \$3.23 billion in January 2008 alone (Wilson & White, 2008). The RBI had increased the repo rate from 6.25% in January 2006 to 7.75% by March 2007. Uneasy about the buildup of inflationary pressures from domestic liquidity conditions and the "high and volatile" levels of international prices on crude oil, food, and metals, it had also increased the cash reserve ratio for banks from 5% in January 2006 to 7.5% in November 2007.⁸ The annualized rate of inflation was approximately 6% at the start of 2007, but had risen to 11.89% by June

⁷ SEBI (Venture Capital Funds) (Amendment) Regulations, 2004; Dated April 5, 2004, and SEBI (Foreign Venture Capital Investors) (Amendment) Regulations, 2004; Dated April 5, 2004. "The restriction of not investing in companies engaged in real estate sector has also been removed." SEBI 2004-05 Annual Report, pp.113-114.

⁸ Reserve Bank of India Bulletin, February 13, 2008.

2008, and consumers faced interest rates that were up 50% from their levels three years previously (Agarwal & Range, 2008). In June and July 2008, the RBI raised the repo rate three times, to a level of 9%, in an attempt to rein in accelerating inflation. The real estate euphoria had died, and between January and June 2008, the BSE Realty Index had already shed roughly 56% of its value.

3. Literature Review

The sustained growth of the Indian economy which stems from the economic and financial reforms in the 1990s fed into the real estate boom in the latter part of the following decade, a boom which was also stoked by the subsequent liberalization of venture capital and FDI norms. It is only recently, then, that real estate has appeared as a critical element in the growth of the economy, significant strategic consideration at the corporate level, and compelling investment opportunity for retail and institutional investors.

Research on this emerging sector of the Indian market is consequently in its nascent stages. Newell & Kamineni (2007) perhaps represent one of the early academic studies on Indian realty as an avenue for investment. For the period 1998-2005, their study gauges the risk-adjusted performance of the Indian realty sector and the potential of diversification from stocks into real estate. Their results show that the realty sector outperformed the overall stock market in the latter half of their study period, and benefits from diversifying into realty declined as returns on realty and non-realty stocks became more highly correlated. In addition to assessing the reasons for the recent real estate boom in India, Vogel (2007) contrasts the divergent growth strategies adopted by India and China – viz., service-based versus manufacturing – and cautions real estate investors that a service-led growth lacks precedence and adds to the uncertainty of the long run success of the approach.

Relatively more research has been conducted on the broader question of return behavior and efficiency in Indian capital markets, although the results are not entirely consistent. Poshakwale (2002) studies the behavior of individual stock returns on the BSE. His evidence does not support the random walk hypothesis, and indicates non-linear dependence and volatility persistence for daily returns on both an equally weighted portfolio and a sample of individual stocks. Sarkar & Mukhopadhyay (2005) study daily returns on four stock market indices and find signs of predictability in the market based on serial correlation and non-linear dependence. In contrast, Chander et al. (2008) report results for stock market indices that are consistent with independent returns and weak-form efficiency. Sehgal & Jhanwar (2008) study the performance of mutual funds, and find no evidence of any economically meaningful short-term persistence. Dicle et al. (2010) report significant international integration of the Indian market, with strong causality from world markets; they argue that this attribute may allow predictability of returns in the Indian market. Their runs test of individual stocks also suggests the existence of non-random behavior, which leads them to question the efficiency of the market.

The present study contributes to the literature on the behavior of Indian stock returns by specifically focusing on the real estate sector. It also adds to the growing corpus of work on long-term memory, the results of which have been mixed. For example, Lo (1991) and Ambrose et al. (1993) do not find evidence of long range dependence in U.S. stock returns. However, Hays et al. (2010) report long-term memory for the S&P 500 and NASDAQ over the tech bubble of the 1990s. Mills (1993) and Huang & Yang (1995) find weak or no evidence of long-range dependence in UK stock returns. Howe et al. (1999) report similar findings for the Pacific Rim stock markets, Lux (1996) for the German stock market, and Berg & Lyhagen (1998) for the Swedish market. In contrast, Sadique and Silvapulle (2001) find evidence of long-term memory in the South Korean, Malaysian, New Zealand, and Singapore equity markets. A study by Henry (2002) suggests the existence of this phenomenon among stock returns in Germany, Japan, South Korea, and Taiwan. More recently, Choi & Hammoudeh (2009) report long-term memory in returns in the oil market. With regard to the real estate sector in developed economies, the early study by Ambrose et al. (1992) of US REIT returns finds evidence consistent with a random walk. Kleiman et al. (2002) employ real estate share prices and report similar results for North America, Europe and Asia. Cotter and Stevenson (2008) study long memory in the volatility of REITs, and report evidence of volatility persistence in US REIT returns (although of a smaller magnitude than that found for the S&P 500 index), and find that this persistence is related to trading volume. Liow (2009), on the other hand, finds weak evidence of volatility persistence for the real estate sector in developed countries such as Australia, Japan, the Netherlands, Singapore, the UK and the US.

Our study uses a period of significant increase followed by rapid decline in the realty index to ascertain whether a measurable long memory effect was present in Indian real estate equities. The presence of such long memory would imply that (a) there are inefficiencies in the Indian financial markets, and (b) there are periods when technical trading rules can afford the investor relatively large risk-adjusted returns. The following two sections describe the data and methodology employed to test for long-term memory in the returns to the BSE Realty and SENSEX indices over the period that covers the recent Indian real estate bubble. The results of these tests are also reported.

4. Empirical Analysis

3.1 Data and Methodology

The daily values for the BSE Realty Index for the period from January 2, 2006 to January 29, 2010 were used to compute the holding period returns for this index. The historical index values are reported on the Bombay Stock Exchange Ltd. [www.bseindia.com]. The daily return series consists of 1006 observations. As noted in Section I, the pattern of the relative values of the BSE Realty Index versus the Sensex Index suggests that real estate equities experienced a bubble which started in 2006 and culminated in 2008, followed by a comparatively mild divergence of the realty index from the broader index until the start of 2010.

In modeling returns, studies of market efficiency have often assumed a normal or approximately normal distribution, and a random walk. The assumption of a normal distribution and finite variance allows the use of traditional mean-variance statistical techniques to obtain an optimal, or unique, risk-return tradeoff. Table 1 presents some tests related to the mean and distribution of the returns on the BSE Realty Index for the 2006-2008 sub-period.

Table 1BSE Realty Index Return Tests: "Bubble Period", January 2,
2006 to December 31, 2008

| Test | Statistic Value | <i>p</i> -Value |
|-------------------------|-----------------|-----------------|
| t-test (mean = 0) | 0.264 | 0.2642 |
| Jarque-Bera (Normality) | 439.744 | 0.0000 |
| Skewness ($Sk = 0$) | -0.421 | 0.0000 |
| Kurtosis (Ku = 0) | 3.668 | 0.0000 |

The assumption that the total sample returns have a zero mean cannot be rejected, but the sample does appear to be non-normal with significant skewness and kurtosis. The results for this period are broadly in line with those of Mandlebrot (1972a, 1972b), who notes that stock returns tend to have higher peaks about the mean, skewness, and fatter tails than in a normal distribution⁹, and are best described by stable Paretian distributions. These, Peters (1996) notes, are "characterized by a tendency to have trends and cycles as well as abrupt and discontinuous changes". Significantly, such distributions have infinite or undefined variance. If returns follow such a pattern, Cootner (1964) admits that "almost all of our statistical tools are obsolete".

 $^{^9}$ The results were similar for the second half of the sample, viz. January 2, 2008—January 29, 2010, except that there was no significant skewness (p=0.679).

Table 2 below provides descriptive statistics for the periods "prior to the spike", "over the spike", and "after the spike" in the BSE Realty Index. It describes the basic distributional characteristics of returns for each period, and indicates non-normality for all periods, but confirms a significant difference in the order of magnitude of returns between the pre-and post spike periods.

| Table 2 | BSE Realty | Index | Descriptive | Statistics: | Various | Periods |
|---------|-------------------|--------|---------------|-------------|---------|---------|
| | Relative to th | e Janu | ary 2008 peal | k. | | |

| Test | "Pre-Spike" Jan. 06-April 08 | "Over the Spike" Sep. 07-April 08 | "After the Spike" April 08-Jan. 10 |
|----------------------------|---------------------------------|---|--|
| Average Daily Return | 0.004 (0.005) | 0.001 (0.770) | 0.001 (0.734) |
| Jarque-Bera (Normality) | 47.524 (0.000) | 16.035 (0.000) | 258.50 (0.000) |
| Skewness (Sk = 0) | -0.324 (0.001) | -0.209 (0.308) | 0.028 (0.813) |
| Kurtosis (Ku = 0) | 1.271 (0.000) | 1.569 (0.000) | 3.729 (0.000) |

Notes: Figures in parentheses are p-values.

In the present study, we employ both the classical rescaled range (R/S) analysis and Lo's MRSA to test for a long memory effect during the post-2006 period¹⁰. Several studies have employed the two techniques to test for the presence of long-term memory in time series (e.g. Mills, 1993; Huang & Yang, 1995; Howe et al., 1999; Mulligan, 2000; Sadique & Silvapulle, 2001; Hays et al. 2010).

3.2 Classical R/S Analysis

Classical R/S analysis has its roots in Hurst's study of non-periodic cycles in the Nile's overflow (Peters, 1994). For time series x with n consecutive values $x = x_1, x_2, ..., x_n$, the mean and standard deviation, x_m , and s_n are:

$$x_m = \frac{\sum_{i=1}^n x_i}{n} \text{ and}$$
$$s_n = \sqrt{\frac{\sum_{i=1}^n (x_i - x_m)^2}{n}}.$$

¹⁰ Studies of long-memory in US stock markets for periods prior to the 1990s do not find convincing evidence of persistence. As noted above, Hays et al. (2010) do find strong evidence of long-memory in the S&P 500 and NASDAQ indices over the 1992-2002 speculative period.

The range is the difference between the maximum and minimum cumulative deviation values over n observations as shown below:

$$R = Max\left[\sum_{i=1}^{n} (x_i - x_m)\right] - Min\left[\sum_{i=1}^{n} (x_i - x_m)\right]$$

This range must be nonnegative, given the fact that x has been redefined to a mean of zero; the maximum must be at least zero, the minimum can be at most zero. Furthermore, the range represents the distance traveled by the system in time n. For systems characterized by the Brownian motion, the distance covered is proportional to the square root of time, T (the "T to the one-half rule"):

$$R = T^{0.50}$$

Hurst defines a more generalized form of this rule that is applicable to time series characterized by dependence rather than the Brownian motion:

$$R/s_n = k \times n^H$$

The left-hand-side represents a "rescaled range", that is, the range divided by the standard deviation of the series, k is a constant, and H is the "Hurst exponent". The expression examines the range of the cumulated deviations from mean scales over the time increment, n. For a random time series, H would assume a value of 0.50.

The logarithm of the above expression yields:

 $\log R/s_n = \log k + H \log n$

Thus, we can estimate the Hurst exponent as the slope of the plot of log R/s_n against log n. It should be noted that, in practice, H is estimated by dividing the series into contiguous subperiods and using ordinary least squares (OLS) to find the value of H^{11} .

If $0.50 < H \le 1$, then the series is "persistent", the system covers a greater distance than that of a random one, elements in the series influence other elements in the series, and there is long memory. If $0 \le H < 0.50$, then the series is "anti-persistent", and the system covers a smaller distance than that of a random process. This suggests that the process reverses itself more frequently than a random process.

The results of the classical R/S analysis on the bubble period are shown in Table 3 below. We also report the results of two additional self-affine fractal

¹¹Peters (1994), pp. 61-63, provides a step-by-step guide to estimating H.

analysis techniques, viz. the roughness-length method, and a variogram analysis.

| Table 3 | Classical R/S Analysis Results: BSE Realty Index: Jan 1, 2006 |
|---------|---|
| | – Dec 31, 2008 |

| Method | H | Standard Error | t | d.f. | <i>p</i> -value |
|------------------|-------|----------------|--------|------|-----------------|
| R/S | 0.582 | 0.0274 | 2.993 | 18 | 0.0078 |
| Roughness Length | 0.524 | 0.0043 | 5.581 | 14 | 0.0001 |
| Variogram | 0.613 | 0.0070 | 16.143 | 72 | 0.0000 |

The roughness-length method is similar to the classical R/S analysis, except that it employs the root-mean-square roughness of the data in windows of length w, S(w), in place of the R/S. This variable is related to the Hurst exponent as follows: $S(w) \approx w^{H}$. The variogram, or variance of increments, of a series y(x) is: $V(w) \equiv [y(x) - y(x+w)]^2$, where w is the distance between two y values in a trace. The variogram is related to the Hurst exponent as $V(w) \approx w^{2H}$ (see Mulligan, 2004). As in the case of the R/S analysis, regression is used to estimate the Hurst exponent via the roughness-length and variogram methods.

The results of the fractal analysis techniques show Hurst exponents significantly greater than 0.50. This suggests that there was persistence in the Indian realty index returns over the three-year window studied, which is consistent with the notion that investors priced securities based on prior return performances, and is evidence of inefficiencies in the market. However, we must for now qualify these conclusions by noting Lo's (1991) critique of the distributional properties of the R/S, which he demonstrated was influenced by the presence of short-term dependence.

3.3 Modified R/S Analysis

Given the concern that the classical R/S analysis is not robust to short-term dependence, we supplement our study of long memory effects with Lo's MRSA. In contrast to the classical tests presented in the previous section, the MRSA is robust against autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) effects, short-term dependence (auto-correlation), non-normality, and heteroskedasticity.¹² Under the MRSA, the range value is calculated as the difference between the maximum and minimum cumulative deviations for the return series:

¹² Tse (1998) finds the MRSA to be "very robust to GARCH effects" in comparison to the widely used Gweke and Porter-Hudak fractional cointegration test.

$$R_n = Max \left[\sum_{t=1}^n (x_t - x_m) \right] - Min \left[\sum_{t=1}^n (x_t - x_m) \right]$$

This range value is the same as that for the classical R/S analysis, except that all observations are used. However, the range is "rescaled" by using a modified variance estimator (S_t^2) which incorporates the weighted autocovariances up to lag q. S_t^2 is equal to the sample variance plus a weighted sum of the autocovariance terms up to a specified lag q, as shown in the following equation:

$$S_t^2 = S_x^2 + \frac{2}{n} \sum_{j=1}^{q} w_j(q) \gamma_j$$

where

 S_t^2 = modified variance estimator that incorporates the weighted autocovariances up to lag *q*;

 S_{*}^{2} = sample variance;

$$\gamma_{j} = \text{autocovariance term for lag } j$$

$$= \sum_{i=j+l}^{n} (r_{i} - r_{m})(r_{i-j} - r_{m}); \text{ and}$$

$$W_{j}(q) = \text{Newey-West (1987) weighting factor for } \gamma_{j}$$

$$= 1 - \frac{j}{(q+1)}, \text{ with } q < n.$$

Unlike the sample variance used in the classical R/S, this modified variance estimator can distinguish between short-range and long-range dependencies¹³. The MRSA test statistic for long-term memory is similar to the classical R/S, except that it employs a modified variance estimator, Q_n , defined as follows:

$$Q_n = \frac{R_n}{S_t}$$

The test statistic, V_n , used in the MRSA is the Q_n statistic normalized by the number of observations:

$$V_n = \frac{Q_n}{\sqrt{n}}$$

The limiting distribution of the modified statistic converges to a standard Brownian bridge, which means that probabilities can be derived for the test statistic value. The distribution function derived by Lo (1991) was used to calculate the *p*-values for the test statistics and these values were checked against the critical values supplied in Lo's study¹⁴. It should be noted that the

¹³ As Lo (1991) notes, the modified variance estimator is robust to many forms of heterogeneity and weak dependence.

¹⁴ The distribution function is found in Lo (1991), p.1292, equation (3.9); critical values are provided in Table II, p.1288 of that study.

modified rescaled range is dependent on the truncation lag q. Yet, it is unclear how best to choose q so as to prevent the finite-sample distribution of the modified statistic from materially deviating from its asymptotic distribution. Consequently, we follow the approach in Lo (1991), and computed the statistic for various values of q. As seen below, our point estimates are quite stable across lag lengths.

The results for the BSE Realty Index reported in Table 4 below indicate that, for the period January 2006 through to December 2008, significant long term memory was present for up to 30 days (or about 6 weeks, with the assumption of 5 trading days per week), with a p-value of 10% or less considered as significant. The long memory effect is strong for lags up to 15 days or 3 weeks where the p-value is about 5% or less. The p-value is below 2.5% for the first 6 trading days in the testing period. Thus, the results of the classical R/S analysis are confirmed by the more powerful MRSA, which is robust with respect to distinguishing between long term and short term dependencies. The presence of a long-term memory effect in real estate returns indicates that the values of the real estate index were a function of past values. This evidence is consistent with the notion that investors were influenced by past returns, a finding that contradicts the idea of market efficiency.

Additional tests were performed to determine whether long-term dependence characterized "pre-bubble" and "post-bubble" periods. No data exist for the realty index prior to 2006, the year of launch. A "pre-bubble" period was defined as January 2006 through to December 2007 – a period ending immediately prior to the peak – and the MRSA results for this time frame are reported in Table 5.

| Lag | Vn | Prob | Lag | Vn | Prob | Lag | Vn | Prob |
|-----|--------|-------|-----|--------|-------|-----|--------|-------|
| 1 | 2.1586 | .0031 | 11 | 1.7800 | .0413 | 21 | 1.6912 | .0684 |
| 2 | 2.0617 | .0065 | 12 | 1.7714 | .0434 | 22 | 1.6862 | .0703 |
| 3 | 1.9824 | .0113 | 13 | 1.7617 | .0459 | 23 | 1.6807 | .0724 |
| 4 | 1.9325 | .0159 | 14 | 1.7511 | .0489 | 24 | 1.6752 | .0746 |
| 5 | 1.8923 | .0206 | 15 | 1.7409 | .0518 | 25 | 1.6693 | .0770 |
| 6 | 1.8682 | .0241 | 16 | 1.7293 | .0553 | 26 | 1.6617 | .0802 |
| 7 | 1.8446 | .0279 | 17 | 1.7173 | .0592 | 27 | 1.6531 | .0840 |
| 8 | 1.8187 | .0327 | 18 | 1.7080 | .0623 | 28 | 1.6436 | .0883 |
| 9 | 1.8006 | .0365 | 19 | 1.7013 | .0647 | 29 | 1.6345 | .0926 |
| 10 | 1.7888 | .0392 | 20 | 1.6961 | .0666 | 30 | 1.6261 | .0967 |

Table 4MRSA Results: BSE Realty Index, "Bubble Period"
January1, 2006 – December 31, 2008

| Lag | Vn | Prob | Lag | Vn | Prob | Lag | Vn | Prob |
|-----|--------|-------|-----|--------|-------|-----|--------|-------|
| 1 | 1.5972 | .1112 | 11 | 1.2611 | .4457 | 21 | 1.2503 | .4610 |
| 2 | 1.4765 | .1972 | 12 | 1.2590 | .4486 | 22 | 1.2569 | .4515 |
| 3 | 1.4052 | .2658 | 13 | 1.2547 | .4547 | 23 | 1.2638 | .4418 |
| 4 | 1.3612 | .3151 | 14 | 1.2497 | .4619 | 24 | 1.2715 | .4311 |
| 5 | 1.3290 | .3545 | 15 | 1.2455 | .4679 | 25 | 1.2784 | .4215 |
| 6 | 1.3052 | .3853 | 16 | 1.2409 | .4744 | 26 | 1.2817 | .4169 |
| 7 | 1.2875 | .4091 | 17 | 1.2375 | .4795 | 27 | 1.2826 | .4157 |
| 8 | 1.2754 | .4256 | 18 | 1.2367 | .4806 | 28 | 1.2812 | .4177 |
| 9 | 1.2680 | .4360 | 19 | 1.2385 | .4780 | 29 | 1.2774 | .4228 |
| 10 | 1.2628 | .4433 | 20 | 1.2438 | .4703 | 30 | 1.2739 | .4277 |

Table 5MRSA Results: BSE Realty Index, "Pre-Bubble Period"
January 2, 2006 – December 31, 2007

Similarly, a "post-bubble" period was defined as January 2, 2008 – January 29, 2010. As can be seen from the graphs for the indices in Figure 1, this time-frame partially overlaps the second part of the "bubble period" for which long-memory results are reported in Table 4, but does not include the spike in the realty index. Table 6 reports the MRSA results for this period.

Table 6MRSA Results: BSE Realty Index, "Post-Bubble Period"
January 2, 2008 – January 29, 2010

| Lag | Vn | Prob | Lag | Vn | Prob | Lag | Vn | Prob |
|-----|--------|-------|-----|--------|-------|-----|--------|-------|
| 1 | 1.6291 | .0952 | 11 | 1.4674 | .2052 | 21 | 1.4120 | .2587 |
| 2 | 1.5852 | .1188 | 12 | 1.4603 | .2116 | 22 | 1.4099 | .2608 |
| 3 | 1.5518 | .1397 | 13 | 1.4572 | .2144 | 23 | 1.4076 | .2632 |
| 4 | 1.5360 | .1506 | 14 | 1.4546 | .2168 | 24 | 1.4044 | .2667 |
| 5 | 1.5261 | .1577 | 15 | 1.4515 | .2196 | 25 | 1.4002 | .2712 |
| 6 | 1.5295 | .1553 | 16 | 1.4456 | .2252 | 26 | 1.3949 | .2768 |
| 7 | 1.5240 | .1592 | 17 | 1.4360 | .2344 | 27 | 1.3891 | .2832 |
| 8 | 1.5090 | .1706 | 18 | 1.4279 | .2424 | 28 | 1.3834 | .2896 |
| 9 | 1.4908 | .1851 | 19 | 1.4208 | .2496 | 29 | 1.3805 | .2929 |
| 10 | 1.4781 | .1958 | 20 | 1.4159 | .2546 | 30 | 1.3776 | .2961 |

A comparison of Tables 4, 5, and 6 suggests that long memory effects are specific to the "bubble" in Indian real estate, a period that encompasses the significant rise and subsequent collapse in the real estate equity values. That is, while the MRSA for the period January 1, 2006-December 31, 2008

indicates significant long-term memory, as indicated by the low p-values, the periods of January 2, 2006-December 31, 2007 (termed "pre-bubble period") and January 2, 2008-January 29, 2010 (termed "post-bubble period"), provide no such indication. For example, for lags of 2 to 14 days, the p-values for the test statistic, V_n , ranges between 0.0065 and 0.0489 for the "bubble period", between 0.1972 and 0.4619 for the "pre-bubble" period, and between 0.1188 and 0.2168 for the "post-bubble" period. The results of this study are quite consistent with Hays et al. (2010), who find that significant long memory effects can be detected for the U.S. stock markets for the period of the tech bubble of the 1990s, but not for periods outside the bubble.

4. Conclusion

India is one of the most significant emerging markets in Asia. As noted in this study, the real estate sector has assumed a position of critical importance within the context of this country's development. In addition, there has been an international increase in appetite for investing in the real estate sector of Asian economies characterized by robust development (Liow, 2007; 2009). Yet, the study of the sector remains in its nascent stages, and the present work constitutes one of the first attempts at analyzing financial asset pricing in this rapidly transforming Indian market.

This study's use of three self-affine fractal analysis techniques and Lo's MRSA reveals the existence of long memory in the BSE Realty Index. Specifically, it documents the presence of long-memory in returns for the January 2006 - December 2008 time span, a period during which the realty index returns display the classic characteristics of a bubble. During this period, particularly strong dependence is found up to fairly long lags of 15 days. However, an investigation of the "pre-" and "post-bubble" periods does not reveal any long-memory. These results are similar to those found in some of the studies on U.S. equity markets (e.g. Hays et al., 2010). More specific to the real estate sector in Asian emerging markets, long memory in volatility is reported by Liow (2009) for Indonesia, Malaysia, and the Philippines. The study notes that since many market players may believe that the 1997 Asian financial crisis has had "a long run effect on the real estate markets' perception of volatilities" the study of long memory is of some importance in the Asian context.

The present study contributes to the general corpus of work on long memory in asset prices, but also potentially has important policy implications. The results cited here suggest that real estate returns, for a while, were spurred on by investor "exuberance" or "bias". During this period, there was a measurable long memory effect, consistent with the notion that investors used past return information to form expectations about present and future returns. This facet of return behavior points to at least periodic inefficiencies in the pricing of equities in this market. Such inefficiencies are of particular concern for developing economies like India that wish to attract international investors (Dicle et al., 2010). Thus, the results of this study should be of interest to policy makers who seek to alleviate constraints on growth by encouraging a steady flow of capital into the real estate sector. Such a flow can be expected to be stimulated by fundamentals; conversely, significant inefficiencies and erratic price upheavals are likely to discourage the desired long-term infusion of capital into this critical sector.

Also significant from a policy standpoint is the possibility that this divergence from market efficiency stems from inadequate transparency among companies. The SEBI, created as part of the economic reform and liberalization process that began in the early 1990s, is considered as a regulator that is fairly rigorous in promoting fair dealings, transparency and best practices (Chakrabarty et al., 2008). Still, there is some evidence to suggest that India is among the more notorious economies in the matter of earnings opacity and management. For instance, Bhattacharya et al. (2003) study 20 developed countries and 14 emerging economies to construct an opacity index based on earnings aggressiveness, loss avoidance, and earnings smoothing. In increasing order of earnings opacity, India ranks 31 among the 34 countries on their list.

The country's accounting standards diverge in many respects from the International Accounting Standards (IAS), provide firms with substantial leeway in financial reporting, and render the interpretation of financial statements quite challenging (Chakrabarti et al., 2008). With specific reference to the real estate sector, a survey by Jones Lang LaSalle (2008) reports that "the unmistakable trend is that transparency is improving in India". Still, their survey classifies the country's realty sector as a "semitransparent market" that is ranked 50th among 82 countries. Anand (2009) notes the weak accounting guidelines for this sector of the Indian economy, where firms might purchase property from numerous subsidiaries, recognize revenue from projects prior to their completion, and book as capital (rather than operating expenses) the interest on loans for acquisition of undeveloped land. A greater risk of corporate governance and transparency problems deals with related parties, as in the case of acquisitions from entities controlled by the purchaser, and from inadequate disclosure of land holdings (Range & Choudhury, 2009). As some researchers have stated, "the opaque financial statements and complex off-balance sheet transactions make it difficult to really estimate how profitable these companies are."¹⁵ To the extent that the inefficiency documented here derives from this opacity, the results point to the need for reform in financial reporting and governance practices among real estate firms in India.

¹⁵ "The Realty Bubble," Nov. 27, 2009 accessed at http://new.valueresearchonline.com

Finally, our findings have implications for modeling and forecasting returns in this emerging market, and technical trading rules. A long memory feature in time series would detract from the accuracy of inferences and forecasts based on traditional linear models (given the independence assumption among the latter). The accuracy of prediction may then be enhanced by the use of autoregressive fractionally integrated moving average (ARFIMA) models in which correlations exponentially decay rather than hyperbolically. For example, the study of oil markets by Choi & Hammoudeh (2009) note the superiority of ARFIMA model forecasts of returns in the presence of long memory. With respect to technical analyses, in which moving averages are frequently employed, the presence of long-term dependence may point to the need for trading rules to incorporate higher-order moving averages (Sadique & Silvapulle, 2001). Of course, given the fact that the detected long-memory appears to be related to the speculative period in Indian realty, a successful exploitation of this dependence would require the ability to recognize and accurately anticipate the stages of a bubble's evolution (Hays et al., 2010), a matter of interest for continuing research¹⁶.

References

Agarwal, S. and D. Dahiya. (2007). Stricter Regulations, Smarter Strategies, *International Financial Law Review: Guide to real Estate*, **26**, 31-33.

Agarwal, V. and Jackie Range. (2008). Bargains Emerge in India: Real Estate Sector Attracts Closer Look as Shares Battered, *Wall Street Journal (Eastern Edition)*, July 16, 2008, C 12.

Ambrose, B., E. Ancel, and M. Griffiths. (1992). The Fractal Structure of Real Estate Investment Trust Returns: The Search for Evidence of Market Segmentation and Nonlinear Dependence, *Journal of the American Real Estate and Urban Economics Association*, **20**, 1, 25-54.

Ambrose, B., E. Ancel, and M. Griffiths. (1993). Fractal Structure in the Capital Markets Revisited, *Financial Analysts Journal*, **49**, 3, 73-77.

Anand, Geeta. (2009). India's New Tech: Real-Estate Companies' Stocks, *Wall Street Journal (Eastern Edition)*, Sep 23, C. 6.

¹⁶ A line of enquiry that holds promise in modeling bubbles applies the science of complexity to markets (Johansen, 2004; Johansen et al., 2000; and Sornette & Zhou, 2006).

Bamzai, Sandeep. (2006). No Stopping Bull Run, *Times of India*, December 8, 2006, 16.

Beinhocker, E. D., D. Farell, and A.S. Zainulbhai. (2007). Tracking the Growth of India's Middle Class, *The McKinsey Quarterly*, **3**, 51-61.

Bhattacharya, U., H. Daouk, and M. Welker. (2003). The World Price of Earnings Opacity, *The Accounting Review*, **78**, 3, 641-678.

Chakrabarti, R., W. Megginson, and P.K. Yadav. (2008). Corporate Governance in India, *Journal of Applied Corporate Finance*, **20**, 59-72.

Chander, R., K. Mehta, and R. Sharma. (2008). Empirical Evidence on Weak Form Stock Market Efficiency: The Indian Experience, *Decision*, **35**, 75-109.

Chaze, Aaron. (2007). Real Estate Reaps Benefits of India's Economic Boom, *Institutional Investor*, **41**, 9, 1-2.

Choi, K., and S. Hammoudeh. (2009). Long Memory and Oil and Refined Products Markets, *The Energy Journal*, **30**, 97-116.

Cotter, J., and S. Stevenson. (2008). Modeling Long Memory in REITs, *Real Estate Economics*, **36**, 3, 533-554.

Dicle, M. F., A. Beyhan, and L. J. Yao. (2010). Market Efficiency and International Diversification: Evidence from India, *International Review of Economics and Finance*, **19**, 313-339.

Hurst, H. E. (1951). Long-Term Storage Capacity of Reservoirs, *Transactions of the American Society of Civil Engineers*, **116**, 770-799.

Hays, P., S. Rajagopal, and M. Schreiber. (2010). Evidence of Long Memory in U.S. Stock Returns: The Case of the 1990s Bubble, *Quarterly Journal of Finance and Accounting*, **49**, 1-18.

Henry, O. (2002). Long Memory in Stock Returns: Some International Evidence, *Applied Financial Economics*, **12**, 725-729.

Howe, J., D. Martin, and B. Wood (1999). Much Ado about Nothing: Long-Term Memory in Pacific Rim Equity Markets, *International Review of Financial Analysis*, **8**, 2, 139-151.

Huang, B., and C. W. Yang. (1995). The Fractal Structure in Multinational Stock Returns, *Applied Economic Letters*, **2**, 67-71.

Johansen, A. (2004). Origin of Crashes in Three US Stock Markets: Shocks and Bubbles, *Physica A*, **338**, 135-142.

Johansen, A., O. Ledoit, and D. Sornette. (2000). Crashes as Critical Points, *International Journal of Theoretical and Applied Finance*, **3**, 219-255.

Jones Lang LaSalle. (2003). Contemporary Trends in the Information Technology Sector.

Jones Lang LaSalle. (2005). Foreign Investment Regulations in Real Estate, Market Research Series: India.

Jones Lang LaSalle. (2006). A Real Estate Investment Future, World Winning Cities Series/Emerging City Winners: India, 1-16.

Jones Lang LaSalle. (2008). Transparency Comes of Age: Real Estate Transparency in India, Real Estate Transparency Index, 1-11.

Kilbinger, S.S. (2007). Real Estate Finance, *Wall Street Journal (Eastern Edition)*, Oct.17, B.12.

Kleiman, R. T., J. E. Payne, and A. P. Sahu. (2002). Random Walks and Market Efficiency: Evidence from International Real Estate Markets, *Journal of Real Estate Research*, **24**, 3, 279-297.

Liow, K. H. (2007). The Dynamics of Return Volatility and Systematic Risk in International Real Estate Security Markets, *Journal of Property Research*, **24**, 1, 1-29.

Liow, K. H. (2009). Long-Term Memory in Volatility: Some Evidence from International Securitized Real Estate Markets, *Journal of Real Estate Finance and Economics*, **39**, 415-438.

Lo, A. W. (1991). Long-Term Memory in Stock Market Prices, *Econometrica*, **59**, 5, 1279-1313.

Lux, T. (1996). Long-Term Stochastic Dependence in Financial Prices: Evidence from the German Stock Market, *Applied Economic Letters*, **3**, 701-706.

Mandelbrot, B. (1972a). Analysis of Non-periodic Long-run Dependence Using the Robust Statistic R/S, *Proceedings of the 1971 Princeton Conference on Information Sciences and Systems*, 155-159. Mandelbrot, B. (1972b). Statistical Methodology for Non-periodic Cycles: from the Covariance to R/S Analysis, *Annals of Economic and Social Measurement*, **1**, 259 -290.

Mills, T.C. (1993). Is there Long-Term Memory in UK Stock Returns? *Applied Financial Economics*, **13**, 303-306.

Mulligan, R. F. (2000). A Fractal Analysis of Foreign Exchange Markets, *International Advances in Economic Research*, **6**, 1, 33-49.

Mulligan, R. F. (2004). Fractal Analysis of Highly Volatile Markets: An Application to Technology Equities, *Quarterly Journal of Economics and Finance*, **44**, 155-179.

Naidu, K., R. Reed, and C. Heywood. (2005). The Impact of Business Outsourcing on Corporate Real Estate in India, *Journal of Corporate Real Estate*, **7**, 3, 234-245.

Newell, G. and R. Kamineni. (2007). The Significance and Performance of Real Estate Markets in India, *Journal of Real Estate Portfolio Management*, **13**, 2, 161-172.

Newey, W. and K. West. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, **55**, 3, 703-708.

Peters, E. (1994). Fractal Market Analysis, John Wiley & Sons, Inc.: New York.

Peters, E. (1996). *Chaos and Order in the Capital Markets* (2^{nd} *edition*). John Wiley & Sons, Inc.: New York.

Pitalwalla, Y. A. (2006). Indian Real Estate: Boom or Bubble? *Fortune International (Europe)*, **154**, 1, 14-15.

Poshakwale, S. (2002). The Random Walk Hypothesis in the Emerging Indian Stock Market, *Journal of Business Finance and Accounting*, **29**, 9/10, 1275-1299.

Range, J., and S. Choudhury. (2009). International Finance: Governance Issues Hit India's Property Firms, *Wall Street Journal (Eastern Edition)*, Feb. 3, C2.

Roy, Debarpita. (2007). Strengthening India's Capital Market: Rising Foreign Direct Investment in Real Estate, *Economic Insight: India, Jones Lang LaSalle*, 1-3.

Sadique, S., and P. Silvapulle. (2001). Long-Term Memory in Stock Market Returns: International Evidence, *International Journal of Finance and Economics*, **6**, 59-67.

Sarkar, N. and D. Mukhopadhyay. (2005). Testing Predictability and Nonlinear Dependence in the Indian Stock Market, *Emerging Markets Finance and Trade*, **41**, 6, 7-44.

Sehgal, S. and M. Jhanwar. (2008). Short-Term Persistence in Mutual Fund Performance: Evidence from India, *Journal of Accounting-Business & Management*, **15**, 90-108.

Sornette, D. and W. Zhou. (2006). Predictability of Large Future Changes in Major Financial Indices, *International Journal of Forecasting*, **22**, 153-168.

Tse, Yiuman. (1998). Fractional Cointegration Tests with GARCH, *Applied Financial Economics*, **18**, 329-332.

Vogel, J. H. (2007). Why India is Not the Next China, *Real Estate Finance*, February 2007, 3-7.