A Fractal Analysis of Market Efficiency For Indian Technology Equities

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INTRODUCTION

This paper employs five alternative methods for estimating Hurst exponent (1951), fractal dimension, and Mandelbrot-Lévy characteristic exponent (Lévy 1925) to examine the fractal character of three information technology equities, Satyam, Tata Consultancy Services, and Infosys. Fractal structure or long memory in equity prices indicate that traditional statistical and econometric methods are inadequate for analyzing security markets. Findings support the weak form of the efficient market hypothesis (EMH), and the more general multi-fractal model of asset returns (MMAR) of Mandelbrot, Fisher, and Calvet (1997).

Using the modified rescaled-range (R/S), which is robust against short-term dependence, Lo (1991) found no long memory in stock prices. Technology stocks are of special interest, because they might be less likely to exhibit long memory than other, less volatile securities. Nevertheless, the high volatility of this equity class makes it an attractive subject for fractal analysis. In applying his modified R/S analysis to equity prices, Lo overturned earlier results based on classical R/S methods finding long memory, but he did not examine the highly volatile technology sector. Mandelbrot (1963a, 1963b) demonstrated that all speculative prices can be categorized in accordance with their Hurst exponent H, also called the self-affinity index or scaling exponent (Mandelbrot et al 1997). The Hurst exponent was introduced in the hydrological study of the Nile valley and is the reciprocal of the characteristic exponent alpha (Hurst 1951). Some security prices are persistent with $(0.50 < H < 1.00)$. These less-noisy series exhibit clearer trends and more persistence the closer H is to one, the more investors in such assets should earn positive returns. However, *Hs* very close to one indicate high risk of large, abrupt changes, as $H = 1.00$ for the Cauchy distribution.

A highly remarkable finding is that by several measures, the three technology equities appear at first to be anti-persistent or mean-reverting with $(0.00 < H < 0.50)$, indicating they are more volatile than a random walk. This indicates the Indian technology sector promotes competition and innovation, and its firms respond to the uncertain environment with experimental and dynamic resource allocation (Eliasson 1991a, 1996, p. 110).Mulligan and Banerjee (2008) found that the CNX information technology index (which includes the three firms analyzed here) was also anti-persistent, and for the CNX index, anti-persistence was statistically significant. Anti-persistence, that is, H significantly below 0.50, strongly disconfirms the efficient market hypothesis, suggesting market participants persistently over-react to new information, behavior which imposes greater price volatility than would be consistent with market efficiency. *Hs* significantly above 0.50 would demonstrate stock prices are not random walks, also shedding some doubt on weak form market efficiency and indicating technical analysis could provide systematic returns. Mulligan and Banerjee constructed statistical hypothesis tests and found the CNX index to be significantly anti-persistent, suggesting it is not efficiently valued by the Indian stock market. In marked contrast to this result, although most estimates of the Hurst exponent for the three equities examined here indicate anti-persistence, formal hypothesis tests show this anti-persistence is generally not statistically significant. Thus, the market values these three widely-held equities in an efficient manner, but does not efficiently value the index which combines them with a variety of other information technology equities.

Any findings of non-normality or non-Gaussian character would have severe implications for pricing financial derivatives. Because the Black-Scholes (1972, 1973) option pricing model assumes normally-distributed prices for

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underlying securities, financial derivatives based on non-normal securities prices could not be priced efficiently with this model. Long memory in equity prices would allow investors to anticipate price movements and earn positive average returns. Fractal analysis offers an alternative to conventional risk measures and permits an evaluation of investment alternatives. Fractal analysis can also identify anti-persistent series, e.g., negative serial correlation. Anti-persistent series should also have much shorter cycle lengths than random walks or trend-reinforcing series.Five techniques for estimating the Hurst exponent are reported in this paper.They are : Mandelbrot's (1972) AR1 rescaled-range or R/S analysis, power spectral-density analysis, roughness-length relationship analysis, variogram analysis, and wavelet analysis.Each method analyzes daily closing prices of the three equities as self-affine traces, providing estimates of the Hurst exponent, fractal dimension, and Mandelbrot-Lévy characteristic exponent.

LITERATURE

This section describes first, the empirical literature applying fractal analysis to capital markets, then discusses a variety of theoretical expectations of fractal behavior in Indian technology equities over the 1990s. Finally, the fractal taxonomy of time series, applied below to interpret the empirical results, is developed.

EMPIRICAL APPLICATIONS OF FRACTAL ANALYSIS

The search for long memory in capital markets has been a fixture in the literature applying fractal geometry and chaos theory to economics since Mandelbrot (1963b) shifted his attention from income distribution to speculative prices (See the literature review in Mulligan and Banerjee 2008).

The modern taxonomy of weak, semi-strong, and strong market efficiency was constructed by Fama (1970). Numerous studies (e.g., Saad et al 1998; Mandelbrot and Hudson 2006) have shown that stock markets trend over time, which is not strictly consistent with efficiency in either valuation or information use. Numerous empirical studies disconfirming market efficiency have been produced, notably by Nicholson (1968), Basu (1977), and Rosenberg et al (1985), although it is often recognized as a valuable benchmark. Normality is a necessary, though not sufficient condition for efficient valuation, thus non-normality of a price series can be taken as disconfirmation of market efficiency (Chan et al 2003; Taleb 2008).

Johansson (2001) and Eliasson (1983, p. 274, 1991b) suggest a non-convergence property, characterized by instability of market equilibria, should be "expected in an economy where information use and communication activities dominate resource use and where technological change in information technology dominates total productivity change through constant systems reorganization" (Johansson 2001, p. 121). This characterizes the technology sector, particularly in India, and contrasts markedly with sectors characterized by less competent, less entrepreneurial firms. In contrast to the business enterprises emphasized in traditional economic and managerial theory, likely to exhibit persistence in equity returns, new economy firms are more likely to display antipersistence.

METHODOLOGY

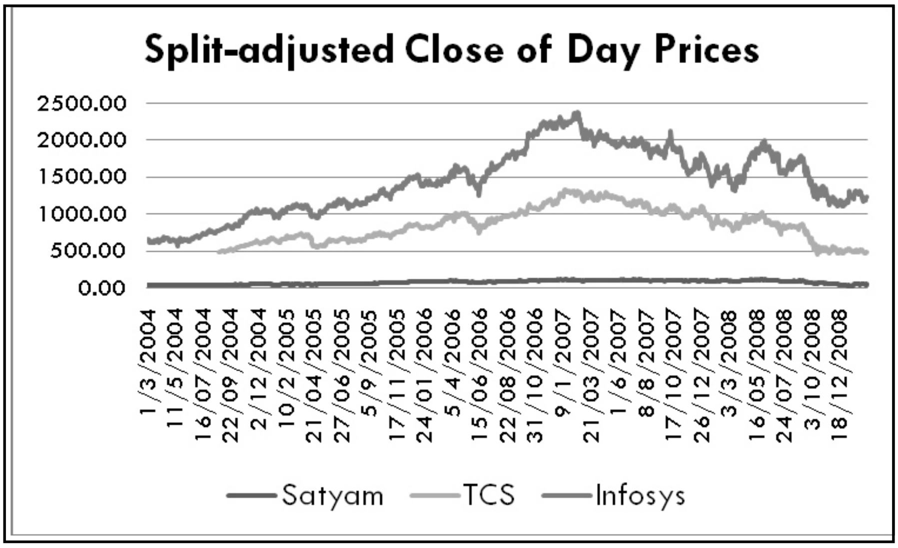
Mandelbrot's (1972, 1975, 1977) and Mandelbrot and Wallis's (1969) R/S or rescaled range analysis characterizes time series as one of four types: **1.)** dependent or autocorrelated series, **2.)** persistent, trend-reinforcing series, also called biased random walks, random walks with drift, or fractional Brownian motion, **3.)** random walks, or **4.)** anti-persistent series. Table 1 provides the taxonomy of time series identified through fractal analysis. Because the Hurst exponent H is the reciprocal of the Mandelbrot-Lévy characteristic exponent α, estimates of H indicate the probability distribution underlying a time series. $H = 1/\alpha = 1/2$ for normally-distributed or Gaussian processes. $H = 1$ for Cauchy- distributed processes. $H = 2$ for the Lévy distribution governing tosses of a fair coin. H is also related to the fractal dimension D by the relationship $D = 2 - H$. In fractal analysis of capital markets, H indicates the relationship between the initial investment R and a constant amount which can be withdrawn, the average return over various samples providing a steady income without ever totally depleting the portfolio over all past observations. Note there is no guarantee against future bankruptcy. If equity series are random walks with $H = 0.50$, returns are purely random and should lead to investors' breaking even over the long run.

Table 1 Fractal Taxonomy of Time Series				
Term	**'Colour'**	**H** **Hurst Exponent**	**D** **Fractal Dimension**	**α** **Characteristic Exponent**
Antipersistent, Negative serial correlation, 1/f noise	Pink noise	$0 \leq H < ½$	$0 < D < 1.50$	$2.00 < \alpha < \infty$
Gaussian process, Normal distribution	White noise	$H \equiv ½$	$D \equiv 1.50$	$\alpha \equiv 2.00$
Brownian motion, Wiener process	Brown noise	$H \equiv ½$	$D \equiv 1.50$	$\alpha \equiv 2.00$
Persistent, Trend-reinforcing, Hurst process	Black noise	$½ < H < 1$	$1.50 < D < 1$	$1 < \alpha < 2.00$
Cauchy process, Cauchy distribution	Cauchy noise	$H \equiv 1$	$D \equiv 1$	$\alpha \equiv 1$
Note: Brown noise or Brownian motion is the cumulative sum of a normally-distributed white-noise process. The changes in, or returns on, a Brownian motion, are white noise. The fractal statistics are the same for Brown and white noise because the brown-noise process should be differenced as part of the estimation process, yielding white noise.				

DATA

The data are daily closing prices reported by the National Stock Exchange of India (NSE) for three firms: Satyam, TCS, and Infosys for the period from March 1, 2004 to February 7, 2009. TCS was only listed from August 25, 2004. This dataset provides 1248 observations over nearly five years (figure 1). The series were adjusted for stock splits to remove the large discontinuities present in the raw data.

Figure 1



The three companies included in this study are in the "Forbes Global 2000" list for 2008, and are in the top five that make up the CNX IT 100 index. These three collectively provide a considerable portion (viz., 61.23%) of the CNX IT 100 index. Although total assets for Wipro (at $3.26B) are more than that of Infosys ($3.08B), TCS ($3.03B), or Satyam ($1.59B), it was not included in the study for two reasons. First, whereas Infosys, TCS and Satyam are relatively new companies in the IT industry, Wipro was incorporated long before the three companies in the sample came into existence. Second, whereas the three companies included in the study started as IT companies, Wipro started as a vegetable oil trading company, which later changed its focus to consumer goods and finally to IT.

In January 2009, it came to light that Satyam had engaged in massive accounting fraud (Timmons and Wassener 2009), overstating its recent revenues by 20% and falsely claiming Rs. 50.4 billion ($1.04 billion) in nonexistent assets.Fraudulent accounting activities introduced profound upward bias on the trading value of this equity during the sample period, but it is interesting that this accounting scandal has no real implications for the efficient market hypothesis. Weak form market efficiency merely asserts that assets are priced in accordance with all publicly available information, and in the absence of public knowledge of the scandal, it appears that Satyam was priced efficiently, though not correctly, up until news of the scandal broke. When information of accounting fraud comes to light, all that market efficiency requires is that the equity be revalued in accordance with the newly acquired information, which certainly occurred in this case.

EMPIRICAL RESULTS

This section discusses and interprets the results of the five alternative fractal analysis methods for measuring the Hurst exponent *H* presented in Table 2.Most measures of *H* range from zero to 0.50 indicating the equity prices are anti-persistent-this would suggest that market participants consistently overreact to the arrival of new information. Mandelbrot, Fisher, and Calvet (1997) refer to *H* as the self-affinity index or scaling exponent.

RESCALED- RANGE OR R/S ANALYSIS

R/S analysis is the traditional technique introduced by Mandelbrot (1972) to measure the Hurst (1951) exponent *H*, characteristic exponent α, and fractal dimension *D*. Time series are classified according to the estimated *H*, which is defined from the relationship

$$R/S = an^H$$

where *R* is the average range of all subsamples of size *n, S* is the average standard deviation for all samples of size *n, a* is a scaling variable, and *n* is the size of the sub-samples, which is allowed to range from an arbitrarily small value to the largest sub-sample the data will allow. Putting this expression in logarithms yields

$$\log(R/S) = \log(a) + H \log(n)$$

which is used to estimate *H* as a regression slope. Estimates of *H* presented in Table 2 suggest disconfirmation of weak form efficiency - all measures indicate *H* is significantly less than 0.50.Measurable anti-persistence demonstrates that market participants habitually overreact to new information, and never learn not to. It also suggests that three firms are competent and entrepreneurial, even though these are large and established, with high capitalization values.

Normality or Gaussian character is a sufficient condition for weak form market efficiency, but not a necessary condition. The result that $H < 0.50$ is generally interpreted as support for the more general multifractal model of asset returns and disconfirmation of the weak-form efficient market hypothesis, which requires $H = 0$. More importantly, findings of $H < 1$ strongly reject weak form market efficiency because they demonstrate anti-persistence. These findings are absolutely fatal to the Black-Scholes (1972, 1973) option pricing model and its underlying assumption of normally-distributed asset prices. Financial derivatives based on non-normal asset prices cannot be priced efficiently. Thus, even if the equity markets for technology stocks are efficient, in spite of substantial empirical evidence against efficiency, the derivatives markets are clearly not efficient. *Hs* different from 0.50 demonstrate that the price series have not been random walks, shedding significant doubt on weak form market efficiency and indicating technical analysis could have provided systematic returns. Nevertheless, this finding may be due to short-term dependence still present after taking *AR1* residuals, or systematic bias due to information asymmetries, or both.

POWER SPECTRAL DENSITY ANALYSIS

Detrended fluctuation analysis (DFA) (Peng et al 1994, 1995) is the method most commonly used in the natural science and econophysics literature for estimating *H.* Henegan and McDarby (2000) found that estimates of *H b*y DFA and power spectral density are related through an integral transform and have similar mean square errors. They conclude that "DFA and spectral measures provide equivalent characterizations of stochastic signals with long-term correlation."It will be seen, however, that the standard errors from this method are extremely high. *Hs* estimated by power spectrum are also in the anti-persistent range $(H < 0.50)$. This method relies on the properties of power spectra of self-affine traces, calculating the power spectrum $P(k)$ *where* $k = 2p/l$ is the wave number, and l is the wavelength, and the logarithm of P(k) versus log(k) is plotted , after applying a symmetric taper function which transforms the data smoothly to zero at both ends. Inspection of these plots revealed a strong linear relationship. If the series is self-affine, this plot follows a straight line with a negative slope -b, which is estimated by regression and reported as β, along with its standard error. This coefficient is related to the fractal dimension by: $D = (5 - \beta)/2$. *H* and *alpha* are computed as $H = 2 - D$, and $\alpha = 1/H$.

Table 2
Estimates of Hurst Exponent H, Characteristic Exponent α and Fractal Dimension D, Various Methods, for three Information Technology Equities 2004 -2009

		Satyam	TCS	Infosys
R/S	H	0.407	0.456	0.466
	α	2.457	2.193	2.146
	D	1.593	1.544	1.534
	s.e.	0.00908	0.0207	0.0132
Spectral Density	β	1.754	1.824	1.883
	H	0.377	0.412	0.442
	α	2.653	2.427	2.262
	D	1.623	1.588	1.558
	s.e.	8.72	5.85	4.71
Roughness-Length	H	0.278	0.401	0.395
	α	3.597	2.494	2.532
	D	1.722	1.599	1.605
	s.e.	0.0038	0.0021	0.00547
Variogram	H	0.477	0.498	0.505
	α	2.096	2.008	1.980
	D	1.523	1.502	1.495
	s.e.	0.178	0.113	0.114
Wavelets	H	0.519	0.485	0.581
	D	1.481	1.515	1.419

ROUGHNESS-LENGTH RELATIONSHIP

This method is similar to R/S, substituting the root-mean-square (RMS) roughness s(w) and window size w for the standard deviation and range. Then *H* is computed by regression from a logarithmic form of the relationship $s(w) = w^H$.As noted in Table 3, the roughness-length method provides the most extreme rejection of weak form market efficiency. Formal hypothesis tests reject the Gaussian null. One difficulty in applying the roughness-length method is that the standard errors are so low the null hypothesis of $H = 0.50$ is nearly always rejected no matter how nearly normal the asset returns. The seemingly unambiguous rejection of weak form market efficiency provided by this technique is best viewed cautiously.

VARIOGRAM ANALYSIS

Variogram *Hs* indicate anti-persistence for Satyam and TCS, but persistence for Infosys, which is the largest and oldest of the three firms studied. The variogram, also known as variance of the increments or structure function, is defined as the expected value of the squared difference between two *y* values in a series separated by a distance *w*. In other words, the sample variogram V(w) of a series y(x) is measured as: $V(w) = [y(x)\quad y(x+w)]^2$, thus *V(w)* is the average value of the squared difference between pairs of points at distance *w* . The distance of separation *w* is also referred to as the lag. The Hurst exponent is estimated by regression from the relationship $V(w) = w^{2H}$.

WAVELET ANALYSIS

This method was developed by Daubechies (1990), Beylkin (1992), and Coifman et al (1992) and is widely used by natural scientists. Wavelet *H* estimates indicate persistence $(H > 0.50)$ for Satyam and Infosys, but anti-persistence $(H < 0.50)$ for TCS. The wavelet method does not provide a standard error for H and cannot be used for hypothesis testing. Wavelet analysis exploits localized variations in power by decomposing a series into time frequency space to determine both the dominant modes of variability and how those modes vary in time. This method is appropriate for analysis of non-stationary traces such as asset prices, i.e. where the variance does not remain constant with increasing length of the data set. Fractal properties are present where the wavelet power spectrum is a power law function of the frequency. The wavelet method is based on the property that wavelet transforms of the self-affine traces also have self-affine properties. Consider *n* wavelet transforms each with a different scaling coefficient a_i, where $S_1, S_2, ..., S_n$ are the standard deviations from zero of the scaling coefficients a_i.

Table 3: Summary of Hypothesis Tests

		Satyam	TCS	Infosys
R/S	H	0.407	0.456	0.466
	s.e.	0.00908	0.0207	0.0132
	t	10.2423	2.1256	2.5758
	d.f.	20	20	20
	p(t)	0.0000	0.0231	0.0090
	null	normal (H=0.50)	normal (H=0.50)	normal (H=0.50)
	alternative	antipersistence (H<0.50)	antipersistence (H<0.50)	antipersistence (H<0.50)
	outcome	reject	do not reject	reject
Spectral Density	H	0.377	0.412	0.442
	s.e.	8.72	5.85	4.71
	t	0.0141	0.0150	0.0123
	d.f.	48	48	48
	p(t)	0.4944	0.4940	0.4951
	null	normal (H=0.50)	normal (H=0.50)	normal (H=0.50)
	alternative	antipersistence (H<0.50)	antipersistence (H<0.50)	antipersistence (H<0.50)
	outcome	do not reject	do not reject	do not reject
R-L	H	0.278	0.401	0.395
	s.e.	0.0038	0.0021	0.00547
	t	58.4211	47.1429	19.1956
	d.f.	14	14	14
	p(t)	0.0000	0.0000	0.0000
	null	normal (H=0.50)	normal (H=0.50)	normal (H=0.50)
	alternative	antipersistence	antipersistence	antipersistence
	outcome	reject	reject	reject
Variogram	H	0.477	0.498	0.505
	s.e	0.178	0.113	0.114
	t	0.1292	0.0177	0.0439
	d.f.	1248	1124	1248
	p(t)	0.4486	0.4929	0.4825
	null	normal (H=0.50)	normal (H=0.50)	normal (H=0.50)
	alternative	antipersistence (H<0.50)	antipersistence (H<0.50)	persistence (H>0.50)
	outcome	do not reject	do not reject	do not reject

Then define the ratio of the standard deviations $G_1, G_2, ..., G_{n-1}$ as: $G_1 = S_1/S_2$, $G_2 = S_2/S_3$, ..., $G_{n-1} = S_{n-1}/S_n$. Then the average value of G_i is estimated as $G_{avg} = (G_i)/(n - 1)$. The estimated Hurst exponent H is computed as a heuristic function of G_{avg}. The Benoit software computes H based on first three dominant wavelet functions, i.e., *n* is allowed to vary up to 4, and *i* for the scaling coefficient a_i is allowed to vary from i = 0, 1, 2, 3.

Table 3 shows hypothesis tests for non-normality. A finding of statistically significant non-normality would disconfirm the weak form of the efficient market hypothesis. The test statistic, computed as the ratio of the estimated Hurst exponent divided by its standard error, is *t*-distributed with degrees of freedom equal to the number of regression observations used to estimate the slope, minus two, the number of regression coefficients estimated. The null hypothesis of normality is that $H = 0.50$. One-tailed hypothesis tests for persistence (H > 0.50) or anti-persistence $(H < 0.50)$ are constructed for each H estimated by R/S, spectral density, roughness-length, and variogram methods. R/S indicates anti-persistence for all three stocks, but this is not statistically significant for TCS, which has seen the most rapid growth during the period under study. Spectral density, which appears to give the best results, finds that the apparent anti-persistence of all three stocks is not statistically significant. Roughness-length significantly rejects the null hypothesis of normality/market efficiency for all three stocks, but this seems to be an artifact of the very low standard error reported for the *H* estimated by this technique. Similarly, variogram analysis fails to reject the null hypothesis of normality/efficient valuation for all three stocks, but this seems to be an artifact of the very *high* standard error.

DISCUSSION

This paper finds little significant evidence of anti-persistence for Satyam, TCS, and Infosys for the 2004-2009 period. This result is broadly consistent with normality of the equity price series and fails to disconfirm the weak form of the efficient market hypothesis. For these large, widely-held, and widely-traded firms, the interpretation suggested is that a large number of market participants face significant incentives to uncover, relay, and act on any information in valuing these equities properly, imposing efficiency.

Equities traded in efficient markets should have Hurst exponents approximately equal to 0.50, indicating prices change in a purely random, normally-distributed manner. Securities with significant secular trends and non-periodic cycles should display time persistence with $H > 0.50$, unless market efficiency imposes randomness and normality anyway. Inspection of the plot of the split-adjusted prices over the period examined reveals secular trends are largely absent (figure 1).Using the same techniques, Mulligan and Banerjee (2008) found that the CNX Information Technology index was *not* efficiently valued. This is particularly surprising considering that the three firms studied here are among the largest in the IT sector and make up a significant portion, over 60%, of the index. The conclusion suggested is that market participants efficiently value some technology equities, though not necessarily all. It should not be surprising that entrepreneurial alertness is focused on the most important stocks with the largest market capitalization. The economical response is to focus attention where it will offer the most benefit at the lowest cost-here, in efficiently valuing the most important firms. It is somewhat surprising that these largest stocks fail to absolutely dominate the stochastic behavior of the CNX index, however, it seems clear that even if the hundred firms in the index are each valued efficiently, it becomes exponentially more difficult to value an index composed of many different equities.

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