A Note On Persistence In Indian IT Equities

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ABSTRACT
The objective of the present study is to test for pricing efficiency in equities of individual information technology companies in the emerging Indian market, where the sector holds an important place in the domestic economy and is a significant contributor to the country's exports. The fifty-six companies currently comprising the BSE IT index are studied for the possible presence of persistence in returns. Employing all continuously available price data for these firms, the Hurst exponent is estimated using three fractal analysis techniques, viz., rescaled range, roughness length, and wavelets. Persistence or "long memory" is unambiguously detected in eleven, or roughly 20% of the return series; antipersistence is detected in the case of two series. The results suggest that not all Indian information technology securities are priced efficiently and that there exists the potential for investors to exploit a long-memory characteristic in those stocks to extract excess profits from trading rules based on historical price information.

KEYWORDS: Pricing Efficiency, Persistence, Hurst Exponent, Indian IT.

ABBREVIATIONS
IT: Information Technology; R/S: Rescaled Range; R/L: Roughness Length; NSE: National Stock Exchange; GDP: Gross Domestic Product; ETFs: Exchange Traded Funds; H: Hurst; BSE: Bombay Stock Exchange.

1.0 INTRODUCTION

This study proposes to assess equity pricing efficiency for IT companies in the Indian economy by considering all firms represented in the BSE IT index. India has experienced strong economic growth since the implementation of its economic liberalization policies in the early 1990s, and there has been an accompanying growth in its IT sector. The competitiveness of this sector has made India one of the largest exporters of information and communication technology services in the world [1]. For instance, between fiscal years 2009 and 2016, the growth in the IT and business process management sector outpaced the overall growth in GDP, increasing the sector's representation in GDP from 6% to 9%, and between fiscal years 2010 and 2018, total exports by this sector increased by as much as 152% [2]. As is the case in many countries, the economy in India is rapidly becoming more technologically intensive, and sustained investments in IT will be of vital importance to ensure continued competitiveness [3]. It can be safely stated that the IT sector in India will continue to play a vital economic role going forward.

In light of the importance and dynamism of the Indian tech sector, it is not surprising that the pricing efficiency among IT equities has been of interest to researchers. Mulligan and Banerjee [4] and Banerjee and Mulligan [5] are two related studies pertaining to this sector and are of particular relevance to the present one. The former study demonstrated the use of fractal analytical techniques in testing for pricing efficiency in an index of Indian IT securities (the CNX IT index). Studying the behavior of that index over the period 1996-2007, it found strong evidence of anti-persistence, which would suggest greater volatility than should be expected for a random walk, and that would be consistent with repetitive overreaction to new information [4]. In a subsequent study, which was a follow-up analysis using three individual technology companies constituting the bulk of the aforementioned index, the authors found inadequate evidence of the same return dynamic as the one observed for the overall index [5]. The authors made a note of the interesting fact that these significant constituent securities did not appear to decide the stochastic behavior of the index of which they were a part. They suggested a reconciliation of the results by pointing out that, led by motives of costs and benefits, investors would tend to restrict their attention to the more "important" equities, i.e., those with the largest capitalizations, and ensure a more informationally efficient pricing of those stocks. Furthermore, they argued that even if each constituent stock were to be priced efficiently, an index comprised of multiple stocks might not necessarily possess the same characteristic, as valuing an index comprised of numerous such equities may be significantly more challenging than valuing individual security; as Banerjee and Mulligan state it, "*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* [5]."

One of the motivations for the present research is the observed contrast in results discussed above for the index on the one hand and for some of its components on the other. Specifically, it prompts the question as to whether *any* of the constituent equities are indeed characterized by anomalous behavior or departures from a strict random walk, which might offer opportunities for abnormal returns at the level of individual security. Neither of the studies mentioned above [4,5] reported a persistence in returns, yet the sector has many more securities whose returns may, in fact, be characterized by long memory. Persistence, or long memory, in a series would indicate that elements in the series influence other elements; that is, the series is "trend-reinforcing", leading to a degree of predictability in returns. Such a feature of equity pricing is inconsistent with informational efficiency in the weak form and would be of interest to traders as trading rules might then be devised to extract abnormal returns. From a broader perspective, informational efficiency (or, particularly, a lack thereof) in this crucial sector should be a matter that concerns policymakers due to its implications for an efficient allocation of resources. The specific objective of the current study is to extend the prior research on individual Indian technology equities in two ways. First, it analyzes the valuation characteristics of *every* current constituent equity in the BSE IT index—numbering fifty-six stocks in all—rather than focus on three IT companies, viz., Infosys, Satyam, and TCS as the previously cited work [5] did—in order to determine whether or not pricing efficiency universally applies to those securities. The study seeks to identify which, if any, of the equities' return series are characterized by persistence or anti-persistence. Toward that end, the returns series of all the IT equities comprising the index are checked for their H exponents. Three approaches are employed for estimating this exponent: R/S, R/L, and wavelet analyses based on which the returns series might be categorized as displaying persistence, anti-persistence, or neither (i.e. no apparent deviation from an unbiased Brownian motion).

As a second extension, this study incorporates *all* price information available for each company, affording roughly 14 years more of daily data for TCS and about 23 years more of daily data for Infosys, two of the three IT firms studied by Banerjee and Mulligan [5]; the third company from that study, Satyam, no longer exists as a distinct entity. The expanded information set would benefit the power of the tests conducted in this study. A study of the tech sector, albeit one that focused on the developed US tech sector [6], estimated the H exponent for a wide sample of 54 individual US technology stocks, classifying their returns series as either persistent or anti-persistent. That early study spanned a period of roughly 7.5 years, beginning in 1993 and ending shortly after the tech bubble. It found evidence of persistence in some series, with anti-persistence being a far more common characteristic for US tech firms. A similar analysis for IT companies is conducted here for the emerging Indian economy, employing all available price data ending in May 2023 for the fifty-six firms in the BSE IT index. Thus, the average number of daily observations per company in this study is roughly 4500, translating to approximately 18 years of data, on average.

An incidental point of interest in a study of the kind proposed here is also that the results would allow at least an informal, qualitative comparison with those reported for the US tech sector by Mulligan [6]. Caporale *et al* [7], discussed briefly in the next section, found stronger returns persistence (higher H values for their index returns series) in the emerging markets they studied versus the developed ones; they suggest the greater implied pricing inefficiency may stem from less liquidity, the presence of fewer market participants, and comparatively less publicly available information (greater information asymmetry) in the less developed markets. While their study has the advantage of a contemporaneous comparison, and such a formal comparative study is not within the scope of the present work, it would be useful as a starting point to document any broad differences observed in the nature of equity returns behavior within the same industry in a developed economy and an emerging market.

This paper represents the development of a very preliminary study mooted in Rajagopal [8] and includes a significant expansion of the data set and methodological approach sketched out in that proposal. The structure of the paper is as follows: The section below briefly reviews the recent literature related to pricing efficiency in Indian markets, especially with regard to efficiency in the weak form. Next, a description is provided of the methodology employed in the study, along with a summarization of the data analyzed. The results of the estimation methods are then presented and discussed. In the final section of the paper, the implications of the study are provided, along with suggestions for possible extensions or avenues for further research.

1.1 OVERVIEW OF RESEARCH ON MARKET EFFICIENCY IN INDIA

The question of efficient pricing of securities, in general, has been of enduring interest not only to traders in search of supernormal profits but also to policymakers on account of the wider implications of efficient markets for the optimal allocation of capital. As will be shown in this section, while there has been a continuing interest over the years in the question of pricing efficiency in emerging markets such as India, the results of efficiency studies have not all been in accord. For example, Badhani [9] adopted a nonparametric approach to study the SandP CNX Nifty index for the period July 1990 to December 2007 and found no evidence of long memory in returns; return volatility, though, did appear to possess a long memory characteristic for the period studied. By contrast, Tripathi [10], employing several techniques, including the R/S method, studied the same index as Badhani [9], though for the period May 2009 to April 2015, and found evidence of long memory. Another study, which covered a five-year period ending in March 2001 and was based on a sample of sixty firms accounting for about 62% of the capitalization of India's equity market, found evidence of long memory in returns for only three companies [11]. The results of yet another study [12] indicated that in the case of two NSE market indices and the ten individual equities studied for the period 1995 to 2005, returns behavior was consistent with a random walk.

In contrast, no evidence could be found of returns on six total indices from the NSE and the BSE following a random walk [13]. The R/S analysis in that study pointed to a significant persistence attribute to the returns series. As the authors noted, their focus was trained on the post-financial reform period in India, viz., 1991 to 2010 [13]. The NSE and BSE sectoral indices were studied over a period roughly covering 2009 to 2014, and the evidence rejected weak-form efficiency across all those series [14]. In a study of the period between January 2010 and May 2018, persistence was observed in eleven sectoral indices [15]. Another work that considered thirty sectoral indices on the NSE and BSE using all available price data ending in August 2017 found evidence of returns persistence or long memory in half of those indices [16].

Aye *et al.* [17] also presented evidence to disconfirm weak form efficiency in the stock markets of the BRICS countries; their results, based on data between 1995 and 2012, suggested significant long memory in stock returns over several time horizons. Studying a more recent period, viz., 2007-2020, Caporale *et al.* [7] found stronger returns persistence for the BRICS countries than for those with more developed markets, suggesting a greater degree of inefficiency and hence greater profit potential for trading rules in the former.

Choudhury and Rajib [18] found qualitatively different evidence; employing the H exponent method and using data between 2006 and 2016 to assess the efficiency of the Indian equity market (specifically, the NSE 50 and the NSE FIN indices), they concluded that based on the H exponents for these series, the Indian market was in fact informationally efficient. Saha *et al*. [19] estimated the H exponent to test for persistence and anti-persistence in equity ETFs and their underlying indices in several countries, finding returns on both ETFs and their underlying indices to be relatively inefficient (primarily exhibiting persistence) in the case of India. Similarly, Sethi and Tripathi [20] reported a fairly prolonged persistence in ETF price premiums over the value of the underlying securities as measured by net asset value; for roughly half the sample ETFs, observed price-net asset value deviations did not dissipate for at least four days.

Even though the results of the studies cited above suggest a lack of perfect consensus regarding weak form efficiency across the Indian markets, long memory (or persistence) does appear to characterize certain segments. As mentioned above, Mulligan [6] studied individual tech stocks in the US using fractal analysis techniques, classifying returns series as either persistent or anti-persistent. In the present work, similar research into possible pricing anomalies, with their attendant potential for excess returns, is attempted in the context of the IT sector in India.

2.0 METHOD(S)

Fractal analysis is a useful tool in testing for persistence as its study of "self-similarity" can reveal how the series of interest scale in time. A discussion of the application of fractal analysis to markets may be found in Peters [21]. A series following a random walk would be characterized by a fractal dimension, d, of 1.5, or a Hurst exponent ("scaling factor"), H, of 0.5. An H exponent greater than 0.5 but less than or equal to 1 would indicate persistence or long memory in the series. This would imply that elements in the series influence other elements in the series ("trend-reinforcing series"). Conversely, an H exponent taking values from 0 to less than 0.5 would indicate a series characterized by antipersistence ("mean-reverting system"), wherein the process reverses more frequently than would be expected for a random series [6]. Thus, H can be taken as a "measure of the bias in fractional Brownian motion" [21].

2.1 CLASSICAL R/S ANALYSIS

The first approach used to estimate the H exponent for the return series is that of the classical rescaled range (R/S) analysis, as suggested by Mandelbrot [22]. Briefly, for a given time series, all possible subsamples are taken, and the average range (R) and standard deviation (S) for each given sample size (n) are calculated. The relationship of the Hurst exponent (H) to the foregoing variables (with k as constant) is:

$$\frac{R}{S} = k \times n^{H}$$

The estimate of H is then derived as the slope of the above relationship in logarithmic form. A detailed description of the steps may be found in Peters [23] and Rajagopal [16], *inter alia*.

2.2 THE R/L APPROACH

The roughness-length (R/L) method is a second approach employed in this study to estimate H. An explication of this method may be found in Mulligan [6], for example. This approach is quite similar to the classical R/S approach discussed above, but rather than employing the vertical range, the R/L method uses the standard deviation (the root-mean-square "roughness") of the data for varying window lengths. In the presence of self-affinity, that (average) standard deviation calculated in a window, s(w), the window interval, w, and H are related as shown below:

$$s(w) = w^H$$

Like in the case of R/S analysis, H is estimated here as the slope of the above relationship in logarithmic terms.

2.3 WAVELETS METHOD

Wavelet analysis is the final estimation process used in this study, and the description of this approach is provided in Mulligan [6], *inter alia*. This method relies on the fact that the transforms of self-affine traces are also self-affine. Briefly, wavelet transforms of the series are taken using different scaling coefficients. The standard deviations of the respective coefficients from zero are measured, and the ratios of those standard deviations are defined; for N transforms, we have N-1 ratios of standard deviations. The ratios of standard deviations are averaged, and a heuristic function approximates the Hurst exponent by that average. As in Mulligan [6], we vary N up to four, using the first three dominant wavelets. A standard error is unavailable in the wavelet method that might allow for a test of the hypothesis for the H exponent.

With regard to the data used to estimate H, all available price information was collected ending on May 31, 2023, for the equities comprising the BSE IT index; considerations of data availability led to the choice of this index. All price data were downloaded from bse.com. Prices were adjusted for stock splits and share bonuses. Following Peters [23], the prices were converted into logarithmic returns before estimating H. The results of the R/S, R/L, and wavelet analyses are presented and discussed in the following section.

Table 1. H Exponent Estimates for BSE IT Equities.

Company	R/S			R/L			Wavelets
	H	s.e.	df	H	s.e.	df	H
3i Infotech	0.529	0.066	38	0.521	0.019	32	0.653
63 Moons	0.541	0.064	44	0.534***	0.007	42	0.563
Accelya Solutions	0.531**	0.012	39	0.481***	0.006	42	0.563
Affle (India) Ltd	0.566***	0.011	22	0.567***	0.003	16	0.690
Allied Digital Services	0.531	0.034	38	0.494	0.012	32	0.584
ASM Technologies	0.456	0.092	38	0.445***	0.004	42	0.472
Aurionpro Solutions	0.559***	0.016	38	0.493	0.015	32	0.549
Birlasoft Ltd	0.537	0.033	49	0.534***	0.007	42	0.557
Black Box Ltd	0.529	0.054	46	0.519***	0.005	42	0.601
C.E. Info Systems	0.417***	0.019	11	0.508***	0.001	6	0.601
Cerebra Integrated	0.511	0.074	49	0.500	0.009	42	0.600
Cigniti Technologies	0.542	0.049	37	0.529***	0.006	30	0.618
Coforge Ltd	0.520	0.021	39	0.489	0.018	34	0.572
Control Print Ltd	0.494	0.043	44	0.424***	0.015	42	0.431

Cressanda Solutions	0.637	0.211	37	0.671***	0.022	30	0.762
Cybertech Systems	0.526	0.039	44	0.491	0.012	42	0.559
Cyient Ltd	0.552**	0.022	44	0.547**	0.018	42	0.564
Datamatics Global	0.486	0.047	38	0.452***	0.007	32	0.541
Digispice Technologies	0.495	0.086	39	0.420***	0.007	42	0.556
D-Link (India)	0.522**	0.009	32	0.458***	0.003	30	0.576
eMudhra Ltd	0.503	0.003	11	0.466***	0.004	6	0.529
Expleo Solutions	0.566***	0.013	38	0.521***	0.006	32	0.601
FCS Software	0.545	0.083	38	0.548***	0.013	32	0.612
Happiest Minds Tech	0.492	0.012	16	0.460***	0.004	12	0.558
HCL Infosystems	0.552	0.062	46	0.545***	0.004	42	0.595
HCL Technologies	0.500	0.017	38	0.438***	0.008	42	0.530
Infosys Ltd.	0.501	0.022	46	0.493	0.007	42	0.581
Intellect Design Arena	0.518	0.071	30	0.527***	0.007	24	0.634
Kellton Tech Solutions	0.498	0.063	49	0.478*	0.011	42	0.566
KPIT Technologies	0.543*	0.022	22	0.552***	0.004	16	0.708
LandT Technology	0.458	0.03	26	0.456***	0.003	20	0.541

***Significant at the 1% level, two-tailed test
** Significant at the 5% level, two-tailed test
* Significant at the 10% level, two-tailed test

Table 1. H Exponent Estimates for BSE IT Equities (contd…)

Company	R/S			R/L			Wavelets
	H	s.e.	df	H	s.e.	df	H
Latent View	0.447**	0.020	14	0.390***	0.004	8	0.736
LTIMindtree	0.512	0.015	30	0.479***	0.004	24	0.552
Mastek Ltd	0.542*	0.023	46	0.533***	0.012	42	0.576
Moschip Tech	0.501	0.106	49	0.459*	0.023	42	0.616
MphasiS Ltd	0.548**	0.020	46	0.556***	0.020	42	0.562
Nelco Ltd	0.529	0.044	53	0.503	0.007	46	0.612
Newgen Software	0.534***	0.012	26	0.511	0.014	20	0.528
Nucleus Software	0.546	0.033	44	0.507	0.006	42	0.608
Onward Tech	0.513	0.027	46	0.487**	0.006	42	0.556
Oracle Fin Software	0.535	0.029	49	0.513	0.009	42	0.577
Persistent Systems	0.508	0.026	32	0.473***	0.007	30	0.593
Quick Heal Tech	0.498	0.048	30	0.511	0.007	24	0.590
R Systems	0.500	0.029	38	0.482**	0.007	32	0.551

Ramco Systems	0.556	0.040	38	0.534***	0.008	42	0.615
Rategain Travel	0.496	0.011	11	0.405***	0.001	6	0.504
Sasken Tech	0.518	0.041	38	0.509*	0.005	32	0.574
Sonata Software	0.551***	0.011	38	0.495	0.007	42	0.575
Subex Ltd	0.554***	0.012	38	0.494	0.015	42	0.613
Tanla Platforms	0.539	0.059	38	0.521***	0.005	32	0.641
Tata Consultancy	0.498	0.021	39	0.458***	0.014	34	0.566
Tata Elxsi	0.534	0.039	46	0.495	0.007	42	0.584
Tech Mahindra	0.560***	0.009	38	0.564***	0.018	32	0.579
Wipro Ltd	0.499	0.071	44	0.560***	0.011	42	0.565
Xchanging Solutions	0.510	0.042	38	0.483***	0.004	32	0.582
Zensar Tech	0.534	0.061	53	0.530**	0.012	46	0.596

***Significant at the 1% level, two-tailed test
** Significant at the 5% level, two-tailed test
* Significant at the 10% level, two-tailed test

3.0 RESULTS AND DISCUSSION

Table 1 above reports the results of the three fractal analytic techniques undertaken by this study. Of the fifty-six stocks in the index, the classical R/S approach indicated that 15, or roughly 25%, of the stocks comprising the IT index exhibit anomalous behavior. The vast majority—virtually all— of these equities had estimated H greater than 0.50, which is indicative of persistence or long memory in these cases. C.E. Info Systems and Latent View were two exceptions, for they appeared to exhibit anti-persistence, with H < 0.50 based on the rescaled-range estimate. Interestingly, these two series (viz., C.E. Info Systems and Latent View) were also among those with the shortest length.

A much larger number of the series revealed behavior inconsistent with weak form efficiency based on H estimated with the R/L method, with 21 series having H > 0.50. Furthermore, as many as 20 had H < 0.50 in total, suggesting anomalous behavior for nearly 75% of the series. As noted by Mulligan [6], and as is evident here, the very low standard errors lead to a more frequent rejection of the null of H = 0.50 under the R/L method. Along the lines suggested by Mulligan and Lombardo [24], this study began by looking for confirmation of the rejection of the null by both the rescaled range and roughness-length estimation techniques. Applying this restrictive rule of thumb, 7 rather than 15 of the original 56 stocks exhibited persistence or long memory: Affle (India), Cyient Ltd., Expleo Solutions, KPIT Technologies, Mastek Ltd., MphasiS Ltd., and Tech Mahindra. H exponents estimated using wavelets also suggested persistence in these series. Four additional companies, viz., Aurionpro, Newgen Software, Sonata Software, and Subex Ltd., for which the R/S method indicates persistence in returns, also had wavelet estimates H > 0.50.

For two companies, Accelya Solutions and D-Link, R/S and R/L gave contradictory indications regarding weak form efficiency, with one suggesting persistence and the other antipersistence. However, the wavelets estimate of H for these two companies indicated persistence in the two series. Chamoli *et al.* [25] compared, among other approaches for estimating the H exponent, the effectiveness of the R/S, R/L, and wavelets approaches. Their study revealed that the estimates of H provided by the R/S and wavelets methods were superior across varying series of synthetic fractional Brownian motion data characterized by a specified H; the two methods provided more robust estimates of H for series of short as well as long length [25]. Taking this into consideration, along with the fact that the series considered here vary significantly in length (N ranging from 247 to 7724), the finding of antipersistence was discounted when indicated solely by the R/L method.

Considering the foregoing, the results for ASM Tech and Control Print are noteworthy; roughness-length indicated that the returns for these two companies were antipersistent, and this finding was confirmed by wavelet analysis, for which the estimated H was also below 0.50. Rescaled-range estimates of the exponents for these two companies were also below 0.50, though not significantly so. Indeed, returns for ASM Tech and Control Print were the only ones under the wavelets method to have estimated H < 0.50.

Taking together the results from all three fractal methods, persistence in returns, or long memory, was indicated unambiguously for eleven, or roughly 20% of the equities in the BSE IT index, with at least two estimation methods pointing to such persistence. Further, for two companies (ASM Tech and Control Print), anti-persistence was indicated by R/L with confirmation from the wavelet method. Finally, for three companies (Accelya Solutions, C.E. Info Systems, and D-Link) R/S and R/L methods contradicted each other. For two of these companies, Accelya Solutions and D-Link, the finding of persistence according to the R/S was confirmed by the wavelets estimate. Confirming the results in Banerjee and Mulligan [5], which tested for efficiency in three specific technology firms, viz., Infosys, TCS, and Satyam, the results of the present study also did not suggest significant persistence or antipersistence for Infosys or TCS, the two from that sample of companies still in existence as distinct entities.

4.0 CONCLUSION AND SUGGESTED FUTURE RESEARCH

This study considered valuation data for the 56 constituent firms of the BSE IT index and tested for the existence of persistence or antipersistence in returns. Of all the equities considered, roughly 75% have returns that seemed not to deviate from a random walk. Thus, the market appears to price a large majority of these equities efficiently. However, for a significant subset comprising about 20% of the firms, results indicated a persistence in returns, or long memory, suggesting repeating patterns separated in time. Additionally, the return series for the two firms were clearly characterized by anti-persistence, indicating that reversal was more frequent than for a random process and that investors appeared consistently to overreact to the arrival of information in these cases.

The results of the present study differ qualitatively from those for the developed US market reported in Mulligan [6], which uses virtually the same sample size as the current study. The incidence of antipersistence appears to be much more common for the US tech sector in that early study. For example, the wavelets approach indicated antipersistence in as many as 20 of the 54 US technology returns series; the same method indicated 2 of the 56 returns series in the current study of Indian IT companies to be antipersistent. Statistically significant antipersistence is seen in 28 firms and 46 firms using the R/S and R/L methods, respectively, in the Mulligan [6] study; the corresponding counts are 2 firms and 19 firms in the present work. Mulligan [6] suggests that the actions of smaller, more nimble and innovative firms who react quickly in a rapidly changing environment, such as that characterizing the technology sector, will tend to cause higher market volatility and be associated with antipersistence in equity returns they are “engines of Schumpeterian creative destruction” [6]. By contrast, firms that are less innovative or entrepreneurial will tend to show persistence in returns. The difference in the results of the two studies just compared could stem from either a wider incidence of innovativeness or entrepreneurial behavior among US tech firms or from the fact that the studies pertain to different time frames and, therefore, catch the industries at different points of their growth or evolutionary stage, or both. Addressing this issue would be a useful line of research. Potentially, policymakers would be interested in the results of such an inquiry if, for example, it appears that regulatory or other institutional constraints are stifling innovativeness in the Indian IT sector.

Another extension of this study is suggested by the fact that there do exist pockets of exploitable pricing inefficiencies within the Indian IT sector. Investors in these cases should therefore be able to anticipate movements in price and employ trading rules to exploit them for excess returns [26]. Of course, a lucrative strategy would require the trader to characterize the specific dependence patterns or repetitions in cyclical movements, and this is suggested as another fruitful area of further research.

An additional interesting extension of the present study would be to identify firm-specific factors that might explain both the departure from a strict random walk for a subset of companies and the precise nature of that anomalous behavior (i.e., persistence versus antipersistence). The question of the role of firm characteristics naturally arises in the context of the results presented here since two companies, ASM Tech and Control Print, appear as exceptions and exhibit antipersistence in returns. In light of the suggested link between size, innovativeness, and antipersistence [6], it is interesting to note that ASM Tech and Control Print, the two companies showing antipersistence, are not the smallest or youngest, but their size (by revenue) does fall below the median. A cross-sectional study would follow a line of inquiry like the one adopted by Brooks *et al.* [27], who tested the link between market capitalization, stock trading volume, and return volatility and the cross-sectional variation in the estimated H exponents for their sample of Australian firms. To judge the usefulness of such an extension, a preliminary analysis is performed here of patterns between the observed return behavior of Indian IT stocks and their market capitalization, trading volume, the existence of derivates on the individual stocks in the sample, and the inclusion of these stocks in the main indices such as the Sensex or the NIFTY. Further, a check is conducted on whether the length of the returns series influences the observed results. Table 2 below lists the information relevant to such an analysis for all the stocks in the sample, and the summary data for those stocks exhibiting persistence and antipersistence are shown in Table 3.

As stated before, all stock price data were downloaded from bse.com. The market capitalization figures are in Rupees, crores and represent free-float market capitalization as of May 18, 2024. Thus, for this preliminary analysis of cross-sectional factors influencing the observed behavior of returns, they represent a rough proxy for firm size. This data was downloaded from moneycontrol.com. The "average volume" represents the average number of shares traded per day over the period January 1, 2023, through May 31, 2023, and is used here as a proxy for trading activity. This data was downloaded from bse.com.

Table 2. Summary Statistics for BSE IT Equities.

Company	Data Start	N	Mkt. Cap.	Avg. Vol.	Index	Options
3i Infotech	04.22.2005	4453	572.04	177089.691	BSE Small Cap	
63 Moons	04.27.1995	6550	999.40	25173.3754	BSE Small Cap	
Accelya Solutions	11.24.1999	5950	631.53	3695.62464	BSE Small Cap	
Affle (India) Ltd	08.08.2019	943	5,822.38	35118.914	BSE 500	
Allied Digital Services	07.25.2007	3921	364.68	29685.4441	N/A	
ASM Technologies	06.13.1994	6109	440.60	8878.68768	N/A	
Aurionpro Solutions	10.25.2005	4294	3,254.95	11990.5244	BSE Small Cap	
Birlasoft Ltd	01.08.2001	5559	9,934.49	154684.602	BSE 500	Yes
Black Box Ltd	03.02.1992	6721	1,047.07	6175.14327	BSE Small Cap	
C.E. Info Systems	12.21.2021	357	2,602.40	18248.8567	BSE 500	
Cerebra Integrated	03.19.2001	5422	89.56	166542.298	N/A	
Cigniti Technologies	12.10.2013	2591	2,130.23	10881.8797	BSE Small Cap	
Coforge Ltd	08.30.2004	4652	27,905.41	40124.9971	BSE 200	Yes
Control Print Ltd	02.18.1994	6484	653.59	4382.34097	BSE Small Cap	
Cressanda Solutions	01.21.2004	2960	509.47	2043286.97	BSE Small Cap	
Cybertech Systems	09.18.1997	6364	206.98	16064.6218	N/A	
Cyient Ltd	09.25.1997	6372	14,286.29	18868.9026	BSE 500	
Datamatics Global	05.07.2004	4724	1,049.02	28084.8883	BSE Small Cap	
Digispice Tech	01.02.1991	6047	56.03	20286.5845	N/A	
D-Link (India)	12.18.2009	3333	581.84	44924.0115	BSE Small Cap	
eMudhra Ltd	06.01.2022	247	1,720.15	25915.3508	BSE Small Cap	
Expleo Solutions	10.26.2009	3360	600.55	3361.93983	BSE Small Cap	
FCS Software	09.21.2005	4265	525.17	2742549.78	N/A	
Happiest Minds Tech	09.17.2020	669	5,827.88	48553.5387	BSE 500	
HCL Infosystems	05.02.1995	6773	200.03	188343.777	N/A	
HCL Technologies	01.11.2000	5840	139,784.15	179469.748	BSE Sensex	Yes

Table 2. Summary Statistics for BSE IT Equities (contd…)

Company	Data Start	N	Mkt. Cap.	Avg. Vol.	Index	Options
Infosys Ltd	05.02.1995	6775	508,715.81	396447.771	BSE Sensex	Yes
Intellect Design Arena	12.18.2014	2091	7,822.75	41429.7708	BSE 500	
Kellton Tech Solutions	05.24.1995	5519	441.76	115327.315	BSE Small Cap	

KPIT Technologies	04.22.2019	1018	24,229.38	153119.547	BSE 500	
LandT Technology	09.23.2016	1655	12,323.84	16277.9427	BSE 200	Yes
Latent View	11.23.2021	377	3,372.71	61896.3352	BSE 500	
LTIMindtree Ltd	07.01.2016	1698	42,560.20	21417.7822	BSE 100	Yes
Mastek Ltd	04.08.1993	7152	3,499.50	9864.0086	BSE 500	
Moschip Tech	01.29.2001	5473	1,099.55	222366.788	BSE Small Cap	
MphasiS Ltd	02.23.1994	7138	19,122.28	21610.3381	BSE 200	Yes
Nelco Ltd	02.01.1991	7724	747.43	14370.1232	BSE Small Cap	
Newgen Software	01.29.2018	1316	5,916.67	22226.4957	BSE Small Cap	
Nucleus Software	11.09.1995	6578	907.28	8109.14613	BSE Small Cap	
Onward Technologies	02.08.1995	6995	438.85	3809.38109	BSE Small Cap	
Oracle Financial	05.28.2002	5199	18,324.55	5090.01433	BSE 200	Yes
Persistent Systems	04.06.2010	3264	35,357.33	14300.7192	BSE 100	Yes
Quick Heal Tech	02.18.2016	1801	657.45	11641.7937	BSE Small Cap	
R Systems Intl	04.26.2006	4218	846.80	17416.2378	BSE Small Cap	
Ramco Systems	10.09.2000	5628	612.56	14145.7908	BSE Small Cap	
RateGain Travel Tech	12.17.2021	359	3,842.60	55571.8711	BSE Small Cap	
Sasken Tech	09.09.2005	4392	1,255.04	1467.04011	BSE Small Cap	
Sonata Software	01.15.1999	6076	9,857.51	20053.7593	BSE 500	
Subex Ltd	07.31.2000	5722	1,651.19	956519.688	BSE Small Cap	
Tanla Platforms Ltd	01.05.2007	4061	6,277.98	53708.4585	BSE 500	
Tata Consultancy	08.25.2004	4655	395,292.70	135688.421	BSE Sensex	Yes
Tata Elxsi Ltd	05.02.1995	6760	24,711.24	26556.5845	BSE 200	
Tech Mahindra	08.28.2006	4151	80,981.02	152027.665	BSE Sensex	Yes
Wipro Ltd	01.25.1991	7471	64,756.68	480172.665	BSE Sensex	Yes
Xchanging Solutions	03.09.2005	4501	330.03	32850.8596	BSE Small Cap	
Zensar Technologies	01.02.1992	7637	7,062.04	134236.519	BSE 500	

In order to assess any possible impact of series length on the observed results, the 11 stocks showing persistence were classified as having series length either below or above the median. A similar analysis was performed for the characteristics of market capitalization and trading volume.

The finding of persistence in the present sample does not appear to be impacted significantly by time series length; the number of observations for 6 of the stocks showing persistence lay below the median (of 4689), while those for the other 5 were above the median. For the 11 stocks in question, the average series length was 4322, and the median was 4294. Market capitalization ("firm size"), however, did appear to be related to the finding of persistence. As many as 9 of the 11 stocks showing persistence had market capitalizations above the median. The results were identical when the total or full-float market capitalization was employed for the analysis. It appears that trading activity, too, may potentially impact the behavior of returns since 7 of the 11 stocks showing persistence have average trading volumes below the median. These results are certainly suggestive, but a more formal analysis with carefully constructed proxies for size and trading activity and a larger sample would be needed to definitively establish or reject the stylistic patterns observed here.

Two additional factors that might impact returns behavior were considered, viz., whether or not derivative securities were available for trade on an individual stock and whether the stock belonged to a major index. Options or futures may, for instance, impact liquidity, volatility, and efficiency in the spot market [28]. Within the constraints of the present sample, no clearly independent effect emerged in this regard. All but 6 of the full sample of stocks belonged to an index—BSE Small Cap, BSE 500, BSE 200, BSE 100, or Sensex. Roughly half of the full sample of firms were in the BSE Small Cap index, while only a quarter belonged to the BSE 500; it may be a reflection of the “size effect” already noted above that even so, as many 5 of the 11 stocks showing persistence belonged to the BSE 500 index and 4 belonged to the BSE Small Cap index. One belonged to the BSE 200 and another to the Sensex. There were 12 stocks from the full sample (so roughly 21%) on which derivatives were traded, and of these, two belonged to the group of stocks showing persistence, which, at roughly 18%, is similar to the proportion in the full sample. The foregoing observations are summarized in Table 3 below.

Table 3. Selected Cross-Sectional Characteristics of Persistent Series.

Company	Series Length	Mkt Cap	Trading Vol.	Index	Derivatives
Affle (India) Ltd	< Median	**> Median**	> Median	BSE 500	
Aurionpro Solutions	< Median	**> Median**	**< Median**	BSE Small Cap	
Cyient Ltd	> Median	**> Median**	**< Median**	BSE 500	
Expleo Solutions	< Median	< Median	**< Median**	BSE Small Cap	
KPIT Technologies	< Median	**> Median**	> Median	BSE 500	
Mastek Ltd	> Median	**> Median**	**< Median**	BSE 500	
MphasiS Ltd	> Median	**> Median**	**< Median**	BSE 200	Yes
Newgen Software	< Median	**> Median**	**< Median**	BSE Small Cap	
Sonata Software	> Median	**> Median**	**< Median**	BSE 500	
Subex Ltd	> Median	< Median	> Median	BSE Small Cap	
Tech Mahindra	< Median	**> Median**	> Median	BSE Sensex	Yes

Several other potential explanatory factors for a cross-sectional analysis suggest themselves. A reduction in information asymmetry, wherein insiders (managers) have superior information regarding firm prospects as compared to the public, would clearly enhance informational efficiency. Thus, certain attributes of the firm’s Board of Directors, such as the Board’s independence, could be a relevant factor; a greater representation of independent directors may promote the monitoring of managers, enhance firm transparency, and reduce information asymmetry [29]. Similarly, the relationship between firm size and H could be analyzed. In addition to the link between firm size and innovativeness (and hence volatility and antipersistence) hypothesized by Mulligan [6] above, the size variable is often used in the finance literature as a proxy for information asymmetry [30] and, like Board independence, may impact the return dynamic through that channel. The apparent association between the incidence of persistence and firm size noted above suggests that this may be a potentially fruitful line of inquiry. Liquidity is yet another factor to be considered since the trading facilitated by greater liquidity would promote informational efficiency and reduce return predictability [31]. As noted previously, Caporale *et al.* [7], in their comparative study of developed and emerging markets, also suggest that greater pricing inefficiency may arise due to less liquidity and greater information asymmetry in less developed markets. The extensions suggested here are left to future work.

PRESENTATION

The present paper stems from the author’s proposal submitted to the International Conference of the Institute for Global Business Research on April 10, 2020, under the title “Returns persistence in IT stocks: A reexamination” [8]. Relying on a more limited data set, the proceedings version presented the skeletal structure of the intended research and provided some very preliminary results that were suggested by one of the three methods used here, viz., the classical R/S analysis.

CONFLICT OF INTEREST

None.

ORCID
SR – Not available.

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