Rescaled Range and Wavelets Analysis of NSE Pharma Equities: Evidence of Fractal Structure

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Abstract

Indian pharmaceuticals have seen a surge in global demand and concomitantly a large inflow of capital. For investors and traders, the question arises whether there are exploitable inefficiencies in the pricing of the securities in this dynamic industry. Employing two fractal analytical techniques to estimate the Hurst exponent of the returns series, we assess the efficiency of valuation in this sector. There is strong evidence of persistence in returns for half of the stocks studied and no credible evidence of anti-persistence in any of the series. The results suggest trend-reinforcing behavior. Our findings are contrary to expectations under the Efficient Market Hypothesis, and are more consistent with a multifractal model of returns. The sector should be of interest not only to investors seeking to benefit from the expected long-term strength in fundamentals of this industry, but also to traders who seek to exploit pricing inefficiencies by identifying patterns in returns.

I. Introduction

A stream of research has taken up issues of nonlinear dependence, chaos, and efficiency within the context of the Indian capital market (see Poshakwale (2002); Sarkar & Mukhopadhyay (2005); Mishra & Mishra (2011); Mishra et al (2011); Mukherjee et al. (2011); Gupta & Yang (2011); Palamalai & Kalaivani (2015); *inter alia*). This effort has provided valuable insights into market behavior in this emerging economy. The present study contributes to this body of work by providing additional evidence specifically on the question of persistence and anti-persistence in returns. There are three primary motivations for the study. First, there is no clear consensus on the existence or absence of long memory in returns in this emerging market so that further study of the subject is warranted. Second, in contrast to the vast majority of past studies that consider broad indices, the present work focuses on the behavior of equities within one industry, viz. the Indian pharmaceutical sector. As MacDonald & Power (1993) suggest, the aggregation involved in indices can confound firm-specific factors, so that results may not necessarily be generalizable to individual stocks. Whereas the Indian pharmaceutical sector has experienced changes in domestic and international regulation, along with a significant surge in demand, no extant study of which we are aware focuses on the behavior of individual equities within this sector, especially from the standpoint of informational efficiency. Third, documenting the nature of long-term dependence in pharmaceutical stock returns should be of interest to potential investors and equity traders in this dynamic industry.

The subject of capital market behavior, or misbehavior, in an emerging market is not merely of academic interest, but is of obvious practical relevance to the investor and trader seeking higher risk-adjusted returns. Firms in this sector, assisted in large part by a surge in demand for generics, have achieved a global presence that has meant high margins, strong cash flows, and significant positive valuation effects. Domestically, higher incomes and enhancement of health care should drive longer-term growth (see Sen & Oberoi (2014)). While very recent compliance issues have negatively impacted earnings and valuations in this sector, the effect is likely to be temporary as firms align quality to international requirements and invest in additional R&D (see E. Chellam (2016)). Further, Donald Trump’s rhetoric against high drug prices notwithstanding, analysts seem to view a Trump presidency as a net positive for the Indian pharmaceutical industry; Republicans typically take a more favorable stance on free-market pricing of drugs, and any likely regulatory maneuver is anticipated to have a marginal impact especially in the face of pre-existing pricing pressures within the US market (see Trivedi (2016)).

The recent medium-term strong performance and the presumably temporary moderation in valuation in the immediate past is captured in Figure I below, which compares the movement in the NSE Pharma Index to the growth in the NIFTY Index over the period January 1, 2001 through December 30, 2016.

Refer Figure I

Figure I reveals that the NSE Pharma index marginally underperformed the NIFTY index for a brief period beginning circa September 2006. Having tracked the broader index closely for a few years following this underperformance, the Pharma index broke away in May 2011, and has outperformed the NIFTY significantly since then. As the figure shows, the pharmaceutical sector's relative performance has been particularly spectacular since 2014. Over the entire period represented in the figure, viz. January 1, 2001 through December 30, 2016, the NIFTY has gained 552%. The NSE Pharma index, on the other hand, has shown almost twice that rise, having advanced 927%.

The remarkable run-up in equity valuations within the pharmaceutical sector over the last several years, and the existence of strong fundamentals suggesting continued growth in the foreseeable future, raises the question of whether security pricing within the sector is efficient, or whether, perhaps driven by exuberant investors, the industry offers exploitable trading opportunities for enhanced risk-adjusted returns. The present study addresses this question by employing two fractal analysis techniques—the Classical Rescaled Range (R/S) Analysis and Wavelets Analysis—to estimate the Hurst exponent and fractal dimension for the returns series belonging to the 10 pharmaceutical sector companies currently comprising the NSE Pharma index. The study is organized as follows: The section below provides a brief review of the recent literature on pricing efficiency with the Indian context. Following this, a description of the methodology is presented, along with a discussion of the data used in the study. Next, the results of the two fractal-analytical techniques are presented and discussed. The concluding section of the paper presents the implications of the study and suggests potential areas for further research.

II. Literature Review

As noted above, several studies have addressed the issues of nonlinear dependence, chaos, and efficiency in the Indian capital markets. While by no means an exhaustive summary, this section highlights some of this research specifically as it pertains to the issue of weak-form efficiency and long memory. In a relatively early study, Poshakwale (2002) studied the returns behavior for 38 of the most actively traded individual stocks on the Bombay Stock Exchange, as well as the behavior of returns for an equally weighted portfolio of 100 actively traded stocks, over the period January 1990 through November 1998. Evidence pointed to the presence of nonlinear dependence and volatility persistence for these returns. Overall, the results of the Poshakwale (2002) study were inconsistent with the notion of pricing efficiency. Sarkar & Mukhopadhyay (2005) found similar results. While they, too, employed daily data, their focus was on price indices rather than individual stock prices. Studying returns behavior beginning January 1986, January 1991, or November 1994—depending on the index in question—through December 2000, they found evidence to suggest that the Indian stock market was predictable, partly on account of serial correlation, nonlinear dependence, and seasonality of volatility in returns. They concluded that the market's predictability did offer investors with some exploitable opportunities.

Mishra et al (2011) studied daily returns on six stock market indices spanning both the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE) roughly over the period 1991 through 2010. Their results were consistent with the presence of nonlinear dependence in all the returns series studied. Their tests disconfirmed the random walk hypothesis for all these returns series. The existence of deterministic chaos, however, was suggested for only two of the six series. The authors concluded that, at least in the short run, where a chaotic structure in returns was observed, market participants could benefit from trading rules to garner excess returns. In contrast to the foregoing studies, the Mishra & Mishra (2011) study suggested that Indian stock indices as well individual stocks did follow the random walk, though there was evidence of nonlinearity. It should be noted, though, that these results, based on weekly rather than daily data covering the period 1995 through 2005, pertained to a total of 10 individual firms and two price indices.

A more recent study of weak form efficiency in the Indian context is that by Palamalai & Kalaivani (2015), who studied a total of 23 sectoral indices from the NSE and BSE, along with the SENSEX and NIFTY. Using daily data, their study found evidence to disconfirm the random walk hypothesis in the case of all the 25 indices considered, suggesting that excess returns might accrue to appropriately- constructed trading rules. These findings are slightly in contrast to Gupta & Yang (2011), whose use of daily, weekly, monthly and quarterly data to test for weak-form efficiency for the period 1997 through 2011 yielded mixed results. Daily and weekly data did reject weak-form efficiency for both sub-periods 1997-2007 and 2007-2011. On the other hand, the use of monthly and quarterly data indicated efficiency for the sub-period 2007-2011 but not for the earlier sub-period 1997-2007.

Comparatively less research exists on the specific issue of long-range dependence in returns within the context of Indian capital markets. Along our current line of enquiry into the presence of persistence in returns, Mukherjee et al (2011a, 2011b) tested for long-range dependence in the SENSEX index for the period 1997 through March 2009. Their results were consistent with the existence of long memory in the volatility of returns, but not in the returns themselves. Badhani (2008) arrived at the same conclusion using the NIFTY index for the period July 1990 through December 2007. Additionally, the latter study found that long memory in volatility did not apply for the sub-period April 2001 through December 2007, which the author saw as an artifact of a structural break in the volatility process itself. Recent research has also considered the question of long memory in markets other than equities. For example, Kumar (2014) studied daily returns of the Rupee versus the USD over the period February 1994 through November 2013. Similar to the work on equity returns cited above, his study found evidence of long memory in volatility but not in the returns themselves (with the exception of one of the three methods he employed which did indicate long memory in the returns series).

The foregoing discussion suggests, first, that there is some disagreement in results with regard to weak-form efficiency in the Indian context, though the balance of the evidence contradicts the random walk hypothesis especially for earlier time windows (such as periods prior to 2007). Second, there is a relative paucity of research into the specific question of long-range dependence in returns, with existing studies largely focusing on broad market indices. As noted by MacDonald & Power (1993), aggregation into indices may confound firm-specific factors, so the same results may not necessarily apply to individual stocks. In light of these considerations, the present study seeks to investigate long-range dependence in returns for individual firms within the dynamic pharmaceutical sector.

III. Methodology and Data

We focus on the ten firms that currently comprise the NSE Pharma Index. Individual firm level daily closing price data were retrieved from the NSE website, nse.com for the entire period for which data are available, ending on December 31, 2016. The sole exception is LUPIN, for which, on account of a discontinuity in the NSE record, data were retrieved from the BSE website (bse.com). The length of the period for which data are available varies across firms. Table I below provides a summary of the data for the returns data employed in the study. The statistics have been rounded either to two decimal places or to the closest whole number.

Refer Table I

It should be noted that the closing price data retrieved from nse.com (and, for Lupin Limited, from bse.com) had to be adjusted for splits and bonus offerings. The summary statistics reported above refer to returns based on these adjusted closing prices. It appears that the returns for all the firms have a moderate to high degree of positive skewness. Given that the reported kurtosis figures in fact measure excess kurtosis, the returns for two of the firms, Aurobindo Pharma and Piramal Enterprises, appear to be highly leptokurtic. The methodology described below does not require the underlying distribution to be Gaussian and is therefore appropriate for the purposes of the present study. We now turn to a brief description of the methods employed to estimate the Hurst exponent.

A. Rescaled Range Method

The classical rescaled range (R/S) method of estimating the self-affinity index, or Hurst exponent, H, is due to Mandelbrot (1972). We may define a time series x with consecutive values $x = x_1, x_2, \ldots, x_n$. Denoting the mean and standard deviation of the series as, x_m, and s_n, respectively, the range, R, is defined as the difference between the maximum and minimum cumulative deviation values over the observations:

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

As x has been redefined to have a zero mean, R must be nonnegative. R is the distance traveled by the system in time n, which, for systems following Brownian motion, is proportional to the square root of time, T:

$$R = T^{.50} \tag{2}$$

Hurst (1951) provides a generalized form of the rule for series with dependence rather than Brownian motion:

$$\frac{R}{S_n} = k \times n^H \tag{3}$$

R/S_n is the rescaled range, k is a constant, and H is the "Hurst exponent". The relationship shows how the range of cumulated deviations from means scales over the time increment, n. For a random series, H would be 0.50. In estimating H, we could recast the preceding relationship as:

$$\log \frac{R}{S_n} = \log k + H \log n \qquad (4)$$

The Hurst exponent can thus be estimated as the slope of the plot of log R/S_n against log n[1]. In the case of a random series or an independent process, H = 0.50. The series is said to be "persistent" if $0.50 < H \leq 1$, indicating that elements in the series influence other elements in the series. The series is said to be "anti-persistent" when $0 \leq H < 0.50$, suggesting that the process reverses itself more frequently than would a random process. Following Peters (1992), we estimate the Hurst exponent with price data converted into logarithmic returns.

B. Wavelets Method

Wavelet analysis is based on the idea that transforms of self-affine traces themselves possess self-affine properties. In this method, we decompose the series in time frequency space and assess variations in power; a Wavelet power spectrum related to frequency by a power law function would point to the existence of fractal properties[2]. The method, which is applicable in the case of non-stationary series, is briefly described below.

We take T wavelet transforms, each with a distinct scaling coefficient, K_i. Let S_i be the standard deviations from 0 of those T scaling coefficients, K_i. Next, let R_i represent the T-1 ratios of the standard deviations. That is, $R_1 = S_1/S_2$, $R_2 = S_2/S_3$, etc. We then estimate the average of the R_i as:

$$R_{AVG} = \frac{\sum_{i=1}^{T-1} R_i}{T-1} \qquad (5)$$

Finally, we estimate the Hurst exponent as H = Φ (R_{AVG}); Φ is a heuristic function that approximates H by R_{AVG} for stochastic self-affine series. In our estimation process, T is allowed to vary up to a value of 4, and i takes the values of 0, 1, 2, and 3 for the scaling coefficients, K_i. Thus, we estimate the Hurst exponent using the first three dominant wavelet functions. This is the same process as that employed in Mulligan (2004). The wavelet method does not yield a standard error for H that might be employed for hypothesis testing.

IV. Results and Discussion

The results of the Classical R/S and Wavelets methods are presented in Table II below. There is strong evidence to suggest that five of the ten firms included in the NSE Pharmaceutical Index are characterized by persistence in returns. These include Aurobindo Pharma, Cadila Healthcare, Divi's Laboratories, Piramal Enterprises, and Glenmark Pharmaceuticals, for which the Rescaled Range Method provides estimated Hurst exponents significantly different from the benchmark of 0.50. The p-values (reported under a two-tailed test of H = 0.50) suggest a particularly strong case for persistence in the case of the first four of these firms, where the null is rejected at the 1% level; the null is rejected at the two-tailed significance level of 10% in the case of Glenmark. The Wavelets Method provides further

[1] Peters (1994), p. 61-63, provides a step-by-step exposition of this approach to estimating H.
[2] The Wavelets method derives from the work of Beylkin (1992), Coifman et al (1992), and Daubechies (1990).

confirmation of this finding; the estimated exponents range from a low of 0.560 (Glenmark) to a high of 0.596 (Cadila).

The Wavelets Method also suggests comparable Hurst exponents for the series belonging to the remaining five companies, viz. Cipla Limited, Dr. Reddy's Laboratories, GlaxoSmithKline, Lupin Limited, and Sun Pharmaceuticals. Here, the estimated exponent ranges from a low of 0.538 (Cipla) to a high of 0.596 (GlaxoSmithKline). However, the Rescaled Range analysis fails to confirm any significant departure of H from the baseline value of 0.50. Lupin and Sun Pharma are the only two firms for which the Classical R/S yields H estimates below 0.50. Even in nominal terms, the estimated H for Lupin is only fractionally below the benchmark. For Sun Pharma, the estimated exponent is somewhat less than 0.50, but the standard error being fairly large, the null is not rejected. As the difference from null is not statistically significant in these two cases, there appears to be no evidence of anti-persistence in the case of any of the pharmaceutical stocks belonging to the NSE Pharma Index.

Refer Table II

Thus, no fewer than half of the firms comprising the NSE Pharma Index exhibit pricing inefficiency. Their returns exhibit trend-reinforcing behavior, and could be said to follow a biased random walk. In these cases, the notion of weak-form efficiency is called into question, and there likely exist opportunities for excess returns based on trading rules that exploit patterns in price changes.

V. Conclusion and Implications

We address the question of pricing efficiency in the Indian capital markets by focusing on long-range dependence in stock returns within one of the most dynamic industries in this emerging economy. Most of the prior studies of this issue in the Indian context have documented long memory in the volatility of returns (e.g. Mukherjee et al. (2011); Badhani (2008); and Kumar (2004), as cited above). However, extant studies essentially focus on broad market indices. Such aggregation of equities may confound firm-specific factors, so that the same results may not apply to individual stocks (MacDonald & Power (1993)). As such, we focus our analysis on individual pharmaceutical firms that comprise the NSE Pharma Index and, in contrast to the stylized fact of long memory in the volatility of returns documented in the studies mentioned above, find evidence that a significant number of returns series themselves exhibit persistence. The results are contrary to what we would expect under the Efficient Market Hypothesis, and are more consistent with a multifractal model of returns such as that proposed by Mandelbrot et al (1997).

These results suggest that technical rules designed to exploit patterns in price changes may be effective in yielding systematic excess returns, at least in the case of a subset of equities within the fast-growing pharmaceutical industry in India. Success, of course, would be predicated on identifying the nature of dependence and incorporating that information into the construction of trading rules. Studying the precise nature of this dependence, and testing the profitability of trades based on rules thus constructed would be a valuable extension to the present study. Additionally, one may wish to assess the robustness of the Classical R/S results presented here to the existence of short-term dependence using a method such as that devised by Lo (1991). Finally, our results raise the question as to why some firms in the sample exhibit long memory characteristics while others do not. An investigation of firm-specific factors that explain this behavior is suggested as another topic for further research.

References

Badhani, K. N., 2008, Long memory in stock returns and volatility in India: A nonparametric analysis, The ICFAI Journal of Applied Finance, 14 (12), 34-53.

Beylkin, G., 1992, On the representation of operators in bases of compactly supported wavelets, SIAM Journal on Numerical Analysis, 29 (6), 1716–1740.

Chellam, E., May 2016, The big story: Can Indian pharma fight back? http://www.thehindubusinessline.com/portfolio/can-indian-pharma-fight-back/article8603910.ece

Coifman, R., M. B. Ruskai, G. Beylkin, I. Daubechies, S. Mallat, Y. Meyer, and L. Raphael (Ed.), 1992. Wavelets and their applications (Jones & Bartlett, Sudbury, MA).

Daubechies, I., 1990, The wavelet transform, time-frequency localization and signal analysis, IEEE Transactions on information theory, 36, 961-1005.

Gupta, R. and J. Yang, 2011, Testing weak form efficiency in the Indian capital market, International Research Journal of Finance and Economics, 75, 108-118.

Hurst, H. E., 1951, Long-term storage capacity of reservoirs, Transactions of the American Society of Civil Engineers, 116, 770–799.

Kumar, A. S., 2014, Testing for long memory in volatility in the Indian forex market, Economic Annals, 59, 75-90.

Lo, A. W., 1991, Long-term memory in stock market prices, Econometrica, 59, 1279-1313.

MacDonald, R. and D.M. Power, 1993, Persistence in UK share returns: Some evidence from disaggregated data, Applied Financial Economics, 3, 27-38.

Mandelbrot, B. B., 1972, Statistical methodology for non-periodic cycles: From the covariance to *R/S* analysis, Annals of Economic and Social Measurement, 1 (3), 255–290.

Mandelbrot, B. B., Fisher, A., and Calvet, L., 1997, A multifractal model of asset returns (Cowles Foundation Discussion Paper No. 1164, Yale University, CT).

Mishra, A. and V. Mishra, 2011, Is the Indian stock market efficient? Evidence from a TAR Model with an Autoregressive Unit Root, Applied Economics Letters, 18, 467-472.

Mishra, R. K., S. Sehgal and N. R. Bhanumurthy, 2011, A search for long-range dependence and chaotic structure in Indian stock market, Review of Financial Economics, 20, 96-104.

Mukherjee, I., C. Sen and A. Sarkar, 2011a, Long memory in stock returns: Insights from the Indian market, The International Journal of Applied Economics and Finance, 5 (1), 62-74.

Mukherjee, I., C. Sen and A. Sarkar, 2011b, Study of stylized facts in Indian financial markets, The International Journal of Applied Economics & Finance, 5 (2), 127-137.

Mulligan, R. F., 2004, Fractal analysis of highly volatile markets: an application to technology equities, The Quarterly Review of Economics and Finance, 44, 155-179.

Palamalia, S., and M. Kalaivani, 2015, Are Indian stock markets weak form efficient? Evidence from the NSE and BSE sectoral indices, IUP Journal of Financial Risk Management, 12 (4), 7-34.

Peters, E., 1992, R/S analysis using logarithmic returns, Financial Analyst Journal, 48 (6), 81-82.

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

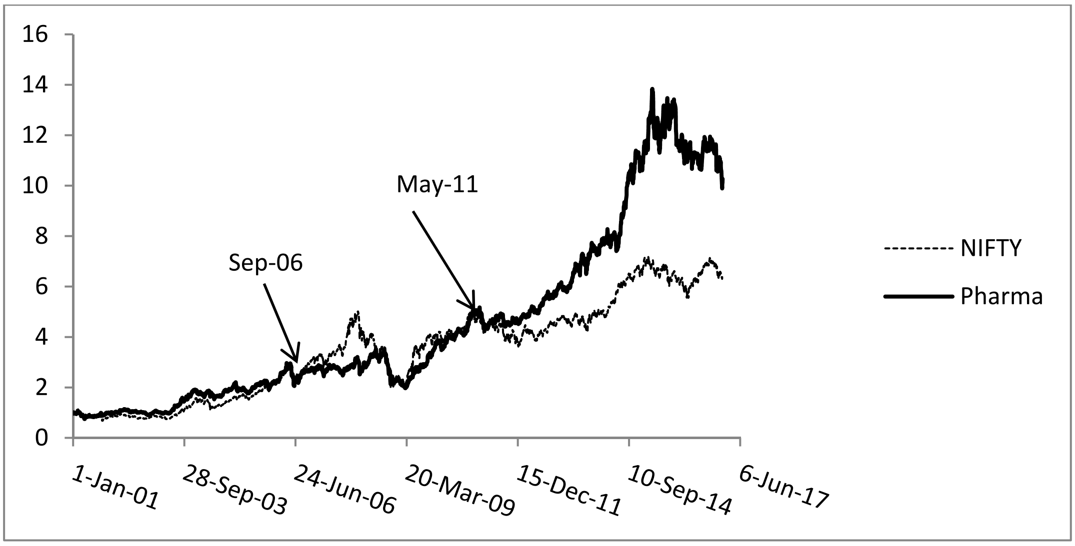
Poshakwale, S., 2002, The random walk hypothesis in the emerging Indian stock market, Journal of Business Finance & Accounting, 29 (9), 1275-1299.

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.

Sen, Sarabjeet and Rahul Oberoi, Feb. 2014, Strong dose: Stocks of pharmaceutical companies had a stellar run in 2013: The trend is likely to continue. http://www.businesstoday.in/moneytoday/stocks/stocks-of-pharmaceutical-companies-performance-2014/story/202657.html

Trivedi, V. S., Nov. 2016, Why a Donald Trump win is good news for Indian drug makers. http://www.livemint.com/Industry/EGHNHLIGfIJ6ZYHyEAtRjN/Why-a-Donald-Trump-win-is-good-news-for-Indian-drug-makers.html

Figure I: NSE Pharma Vs. NIFTY
(Values Indexed to 1 as of January 1, 2001)



Source: National Stock Exchange, nse.com

Table I: NSE Pharma Index Component Stocks
Descriptive Statistics for Stock Returns
(Data Ending December 31, 2016)

Company	Data Start	# Obs.	Mean	Std. Dev.	Skew.	Kurt.
Aurobindo Pharma	01/01/99	4489	5582	9018	2.13	3.01
Cadila Healthcare	27/04/00	4154	1175	1088	1.23	0.59
Cipla Limited	01/01/96	5230	8191	6886	0.90	-0.03
Divi's Laboratories	12/03/03	3435	8224	6686	0.95	0.05
Dr. Reddy's Laboratories	01/01/96	5230	2180	2008	1.32	0.68
GlaxoSmithKline	01/01/99	4485	1456	964	0.59	-0.84
Glenmark Pharmaceuticals	10/02/00	4201	6398	5738	0.79	-0.29
Lupin Limited	10/09/01	3811	4691	5613	1.34	0.54
Piramal Enterprises	01/01/99	4485	1876	1752	1.95	4.63
Sun Pharmaceuticals	01/01/96	5230	23603	32622	1.56	1.15

Source: National Stock Exchange, nse.com & Bombay Stock Exchange, bse.com

Table II: Estimated Hurst Exponents
NSE Pharma Index Component Stocks

	Rescaled Range Method			Wavelets Method	
Company	**# Obs.**	**Est. H**	**p-value**	**# In Trace**	**Est. H**
Aurobindo Pharma	4489	0.580	0.0000	4096	0.587
Cadila Healthcare	4154	0.543	0.0064	4096	0.596
Cipla Limited	5232	0.511	0.6961	4096	0.538
Divi's Laboratories	3435	0.555	0.0000	2048	0.579
Dr. Reddy's Laboratories	5232	0.504	0.9208	4096	0.586
GlaxoSmithKline	4485	0.517	0.4233	4096	0.596
Glenmark Pharma	4201	0.525	0.0600	4096	0.584
Lupin Limited	3811	0.493	0.8039	2048	0.568
Piramal Enterprises	4485	0.526	0.0064	4096	0.560
Sun Pharmaceuticals	5230	0.469	0.5035	4096	0.551

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