Optimal investment horizons for S&P CNX Nifty and its components

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Abstract

The distributions of the first passage time for the S&P CNX Nifty and its 50 constituent stocks are examined. Numerical analysis shows the 'optimal' investment horizon at 5% return level is about 15 days for the index and is most frequently distributed at seven days (range: 5 to 15 days) for the 50 constituent stocks. This suggests a complex dynamics between the index and its constituents in terms of feedback and feed-forward loops. We also examine the distribution of first passage times for six world indices, the Dow Jones Industrial, Hang Seng, FTSE, SSEC, Kospi and the Nikkei. These range between 13 days (for the Kospi) to 47 days for the FTSE. Two distinct regimes, for both positive and negative returns) are observed in the evolution of the optimal investment horizon over different return levels.

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Stochastic finance is a relatively recent field. It was not until 2000 that the full complexity of financial markets was recognized and documented [1,2]. In this paper, we study the distribution of first passage times for the S&P CNX Nifty, and its 50 constituent stocks. The concept of the 'first passage time (FPT)' follows from the 'first passage problem' in the mathematical literature.

The first passage time can be defined as the time at which the observation of any process *first* reaches a particular threshold or barrier. First passage times have been widely used in biological contexts (e.g., time when the size of a population first reaches a threshold of sustainability or unsustainability), and in the physical sciences, particularly early in turbulence studies in fluids and gases (the time when a flow makes the transition between smooth to turbulent, and vice versa) [1,2,3,5,6].

Physicists' interest in financial markets follows naturally from their interest in disordered systems, and complexity. The intricate character of financial markets has been one of the main motives for the physicist community's interest in the study of the statistical and dynamical properties of traded asset markets. This has blossomed into the emerging interdisciplinary field of Econophysics, which applies statistical physics and complex system theories to economics [1-7]. A close analogy between financial markets and turbulence in fluids and gases has been proposed [2,7].

In traded asset markets, the FPT can be extended to the time when an index or an asset price first reaches a pre-set level. Clearly, the distribution of time intervals may have important information about the markets and it is worthwhile for us to investigate these properties extensively [8].

In [9,10], the first passage time in traded markets has been discussed from a statistical physics perspective. In [12], this perspective was extended to a general market user/trader's view by asking the question: "What is the typical time span needed to generate a fluctuation or a movement (in the price) of a given size?" Obviously, the 'waiting time', which is the time *before* the object of observation will first cross the threshold, will follow a probabilistic distribution. The authors in [11], with a background in the physics of turbulent fluids, proposed to call this statistic an 'inverse statistics'. Such 'inverse statistics' of the FPT were reported for the Dow Jones Industrial Average in [13-15] and in the foreign exchange markets [16]. A compact summary of this field can be found on the website of one of the authors.[1]

The rest of the paper is organized as follows. In Section I, we list the implications of this study, from a trader/market user's perspective. In Section II, we present a (non)-exhaustive survey of the literature, followed by methodology in Section III. The main observations and results are presented in Section IV, and Section V concludes

I. Implications

The implications of the proposed study are manifold, and will be useful for understanding the microstructure of the Indian equity markets. Though in the realm of a probability distribution, an insight into the distribution of first passage time is key to timing trades, and by extension, to determining the risk of a trade. Investors may find such an understanding useful in formulating capital and asset allocation strategies, as well as tuning entry and exit strategies. Further, a deeper understanding of the probability

[1] I. Simonsen, http://web.phys.ntnu.no/~ingves/Science/Research/

distribution has great significance for traders in options, on the index and in the constituent stocks, and for refining stop loss strategies.

Studies of the first passage time (and its complementary measures, the waiting time and the optimal investment horizon) are important from an economic point of view in several ways. To quote [11]:

> "Firstly, say an investor plans to sell or buy a certain asset. Then, of course, he or she is interested in doing the transaction at a point in time that will optimize the potential profit, i.e. to sell for the highest possible price, or, for a buyer, to buy for the lowest price. However, the problem is that one does not know when the price is optimal. Therefore, the best one can do, from a statistical point of view, is to make a transaction at a time that is probabilistically favorable. This optimal time, as we will see, is determined by the maximum of the first passage time distribution, i.e. the most likely first passage time.
>
> Secondly, for a holder of an European type option, either a call or a put of given strike price, the most likely first passage time will, in much the same way as presented above, define the optimal maturity of the option. Furthermore, for an American type call option the most likely first passage time of the underlying asset will be useful to know when to exercise the option. These same arguments apply even more to exotic options used in the financial industry.
>
> Thirdly, the investment distribution for negative levels of returns, provides crucial information for the implementation of certain stop-loss strategies.

Finally, but not least, the first passage distribution will by itself give invaluable, non-trivial information about the stochasticity of the underlying asset price."

Unquote

No such study has been conducted on the Indian equity or foreign exchange markets, and therefore, the proposed study for the cash segment of the Indian equity markets should be interesting for all market participants. From an Indian equity markets perspective, we wish to add the following tentative applications of the proposed study:

Market development: The results of the proposed study may be useful to fine tune the tenor of contracts or even introduce new products in the futures and options segment with varying maturity profiles. Such products, traded or synthetic, can be closely aligned to the optimal investment horizon. At a macro level, panel studies (as in [17]) may provide clues to the stage of development of the markets. This may come in handy while arguing for the introduction of equity market products and services.

Investor interest: Investors will find this study potentially useful and reassuring. As noted earlier, in terms of negative returns, investors can build and operate flexible stop loss strategies or contrarian strategies to minimise the loss. Active investors may find it more profitable to explore networks of securities (with or without the index) to maximise return over their preferred investment horizon. This may, however, require an active trading/portfolio realignment strategy. In [38], concepts of entropy transfer have been applied to information flows between stocks and the index, and between networks of indices.

Exotic options pricing: The limitations of the Black-Scholes model for pricing options are well documented. Stochastic volatility (SV) models are computationally demanding. Such models also require a delicate calibration procedure to tune the parameters to market dynamics. To get around this problem, a few *ad hoc* models have been proposed, wherein an analytically derived adjustment for the convexity ("Volatility smile") is made to the theoretical (Black-Scholes) prices. One such model is the Vanna-Volga model which specifically takes into account the survival probability and the *first exit time* [18, 19].

In this case, the first exit time is defined as the minimum between: (i) the time in the future when the underlying price is expected to exit a barrier zone before maturity, and (ii) maturity, if the underlying price has not hit any of the barrier levels up to maturity. The current study on first passage times can be used in modeling 'exit times' and inversely, in setting up the barrier levels.

II. Literature Survey

It may be useful to trace some history of modern financial economics and stochastic finance. Writing his doctoral thesis in 1900, ambitiously on a theory of speculation, a French scientist, Louis Bachelier, proposed a random walk hypothesis for price trajectories [20]. This is perhaps the single most influential starting point in our attempts at understanding the layers of complexity in traded asset prices. A random walk is a path composed of many independent, random steps. The path of a microscopic particle suspended in a viscous fluid is seemingly a random walk process, technically called a Brownian motion, after the Scottish Botanist Robert Brown. Bachelier assumed stock price dynamics as a Brownian motion without drift. While building up this thesis, Bachelier also happened to derive most of the theory of a diffusion processes, ironically, five years before Einstein's classic paper [21].

Now, if a number of walkers start walking randomly (in two dimensional space) from a starting point, their final locations after a fixed time will typically follow a Gaussian distribution: the famous bell-shaped curve. Bachelier has been credited with working out the first-passage distribution function for such a drift-free Brownian motion case. Later, this work became celebrated in the literature on kinetic theory of gases [22].

Despite its robust beginnings, studies on first passage times seem to have fallen into disrepute, for being either too theoretical or too naive. The last two decades has seen a rapid explosion in the application of this concept in diverse fields, such as Biology [23], population studies [24], neural sciences [25], engineering mechanics [26], insurance [27], in turbulence studies [28-33] and in finance.

In studies on turbulent flows in fluids, the first attempt was made in [11] to invert the standard paradigm of measuring velocity difference against distance. To quote:

> "We propose an alternative formulation of structure functions for the velocity field in fully developed turbulence. Instead of averaging moments of the velocity differences as a function of the distance, we suggest to average moments of the distances as a function of the velocity difference. This is like an 'inverted' structure function, with a different statistics."

In a seminal paper [12], the authors aligned the theoretical literature closer to the practical utility in the financial markets by asking the following 'inverse' question: "What is the typical time span needed to generate a fluctuation or a movement (in the price) of a given size by, say, 10%?" This is further explained as "Given a fixed log-return barrier, ρ, of a stock or an index as well as a fixed investment date, the corresponding time span is estimated for which the log-return of the stock or index for the first time reaches the level ρ. This can also be called the first passage time through the level (or barrier) ρ. Correspondingly, the time which the index or stock return spends between a pre-set level and the return to that level is called the waiting time.” [12]

Specifically in the financial markets, the Dow Jones Industrials (DJIA) in the US has been extensively studied in refs. [12-15]. Similar studies have been reported on the foreign exchange markets [16], and on the (German) bond and Italian government bonds [34-36] traded on the for London International Financial Futures and Options Exchange (LIFFE).

In [17], the authors considered a large sample of 40 equity exchange indices around the world, while focusing their attention on the characteristic optimal horizons of the Shanghai Stock Exchange Composite, A Share Index, B Share Index, and 55 stocks listed in Shanghai Stock Exchange and Shenzhen Stock Exchanges. The ambitious scope of this study opened a subsidiary research interest in the nature of the markets: mature versus emerging, investment oriented versus speculative.

III. Methodology

With a defined investment date t, define a level of expected returns as ρ_t. This generic definition includes positive returns ρ_t^{+} and negative returns ρ_t^{-}. The first passage problem can, therefore, be stated as identifying the time τ_ρ at which the returns *first* cross the threshold of ρ_t[2]. It will be useful to define the (log) returns of the series between investment time *t* and τ (dropping the subscript ρ):

$$r_\tau = \ln(s_{t+\tau}) - \ln(s_t) \tag{1}$$

For the time series of interest, and a constant level of expected returns (ρ_t), one obtains a distribution of first passage times (τ_ρ) such that $r_\tau \geq \rho_t$. The maxima of this distribution indicates the highest frequency of occurrence, and is defined as the optimal investment horizon.

The time series of the S&P Nifty and its 50 individual component stocks is available in the public domain. The stock price series were adjusted for stock splits, dividends and bonuses etc. The S&P CNX Nifty series was taken for the period January 02, 1995 to April 29, 2009 (both inclusive), leading to 3574 data points. Only 24 of the constituent stocks have been in the index since the beginning of the study period. The other 26 were taken from the date they were included in the index.

As can be seen from Chart 1, the time series of the index shows a distinct upward drift, particularly pronounced after July 01, 2003. This drift, which reflects general market moods (such as a bull phase or a bear phase), needs to be removed. A de-trended time series would, therefore, strip the original series of market-wide variables, while retaining only the index (stock) specific variables, which are of interest to us.

The drift component can be removed in many ways, the easiest being to remove a moving average from the time series. Alternatives could be a geometric mean or a

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[2] It must be stressed that the returns are not a summation of the daily returns, over all days, leading to τ_ρ.

suitably defined local function. However, the choice of a function and the local window size to which it is localized is arbitrary, and cannot be defended on *a priori* grounds.

In recent years, wavelet transforms have emerged as the vehicle of choice. The underlying logic is that a time series can be hierarchically decomposed into several levels of wavelets (small waves). We define a sequence of resolutions labeled by the integer j such that all details of the signal on scales *smaller* than 2^{-j} are suppressed at resolution j. More and more details are removed as the resolution gets coarser and coarser[3]. Correspondingly, as the resolution gets finer and finer, it is possible to recover the entire function space [37]. The decomposition of the original Nifty series at various levels is illustrated in Chart 2.

The time series of the index (S&P CNX Nifty) and each of its constituent stocks is detrended as discussed above, with a choice of decomposition levels. The original series of the index is presented in Chart 3, with an overlay of the trend, and the detrended series in the lower plate.

In the second step, a threshold is set, say at 5% or 10%. The choice of a starting threshold is arbitrary, but should not be set too low (when it will capture only the noise in the system). The threshold should not be set too high, because the relative lesser numbers of qualifying events will defeat the purpose of obtaining a distribution.

Next, a probability distribution for the set threshold return is drawn from the data. The peak of this distribution is the optimal investment horizon for the series (index or stock).

[3] Interested readers may refer to the Wolfram Research Inc. (*Mathematica)* website for an accessible introduction to wavelets
http://documents.wolfram.com/applications/wavelet/FundamentalsofWavelets/1.1.html

IV. Results and analysis

To present the numerical results of this study, we set the expected returns (ρ_t) at $\pm$ 5% (or 0.05). The distribution of the first passage time for the S&P CNX Nifty for both positive and negative returns, set at 5% is presented in Chart 4. The distribution shows a well defined maxima at close to 15 days for +5% returns and seven days for -5% returns, and an extended tail, which implies a non-zero probability at large times. Note also that the distribution of the negative returns at 5% is shifted to the left of the return for positive returns in the region left of 100 days (the x-axis is logarithmic scaled). This implies that a fall in the index happens at a quicker pace than a rise of the same percentage.

For completeness, we have also considered the Dow Jones Industrial Average (DJIA) for the period October 01, 1928 to April 30, 2009, the Hang Seng (from December 31, 1986 to April 30, 2009), the Kospi (July 01, 1997 to April 30, 2009), the FTSE (April 02, 1984 to April 30, 2009), China's SSEC (from Jan 04, 2000 to April 30, 2009), and the Nikkei 225, from Jan 04 1984 to April 30, 2009. The time series were obtained from the *Yahoo finance* website. The distributions are illustrated in Chart 5a, and the maxima of the distribution, corresponding to optimal investment horizons, are reported in Table 1. The distributions show a similar well-defined maxima, with the peaks distributed between 13 days for the Kospi and 47 days for the FTSE-100. For the DJIA, we find a maxima at 39 days, whereas [12] reported approximately 15 days. The distributions are plotted on a log-log scale in Chart 5b, and the similarity in the power law behaviour of all the seven indices becomes very apparent.

We further analyse the behaviour of the optimal investment horizon for the index (S&P CNX Nifty) as a function of the return level between 3% and 15%. Two distinct scaling regimes can be observed in Chart 6, indicating a regime shift in investor trading patterns when returns crossover at 6% and at -8%.

We now turn to the individual components of the S&P CNX Nifty. A frequency distribution of the maxima of first passage times (optimal investment horizons) of all the 50 stocks is presented in Chart 7, and presented in Table 2. The maxima is distributed most frequently at seven days. This is an interesting finding, for two reasons. One is that seven trading days does not correspond to any trading patterns, pivoted on day of the week etc. Two, the most frequent maxima at seven days for the 50 constituent stocks and approximately 15 days for the index (S&P CNX Nifty) suggests a more complex dynamics between the index and its constituent stocks. From a statistical physics perspective, it would be interesting to examine the relative weights of liner and non-linear dependencies between the two systems, but such a study is outside the scope of this paper.

Purely from an anecdotal viewpoint, we find no evidence of the optimal investment horizon for individual stocks related to the industry classifications. For instance, in the cement industry, ACC returns an OIH of 6 days whereas Ambuja Cements returns nine days. Within the banking industry, SBI (9), ICICI Bank (7), HDFC Bank (9) and Axis bank (5), and within the IT space, TCS (14), Infosys Technologies (7), Wipro (5) are similar examples.

V. Conclusions

The first passage times of the S&P CNX Nifty and the 50 constituent stocks were examined. At the return level of 5%, we find that the distribution of the first passage times for the S&P CNX Nifty presents a distinct maxima at 15 trading days, which is the optimal investment horizon for the index. Six other major global stock indices were examined. This study finds that the optimal investment horizons for the 50 Nifty constituent stocks lie between four days and 15 days. This divergence suggests a complex dynamics between the constituent stocks and the index. We propose to examine the relative weights of the linear and non-linear dependencies between the index and its constituent stocks in later work.

The existence of two distinct regimes in the scaling of the optimal investment horizon relative to the return level is interesting. The finding suggests a marked shift in investor trading behaviour at the crossover point, which was numerically found at 6% for positive returns and 8% for negative returns. We can offer no rigorous or even intuitive analysis of this finding, and is certainly a fit observation to research further.

We are extending this analysis to examine the network of constituent stocks and the index, and particularly to investigate the components of the 'optimality' structure (work in progress).

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Ends

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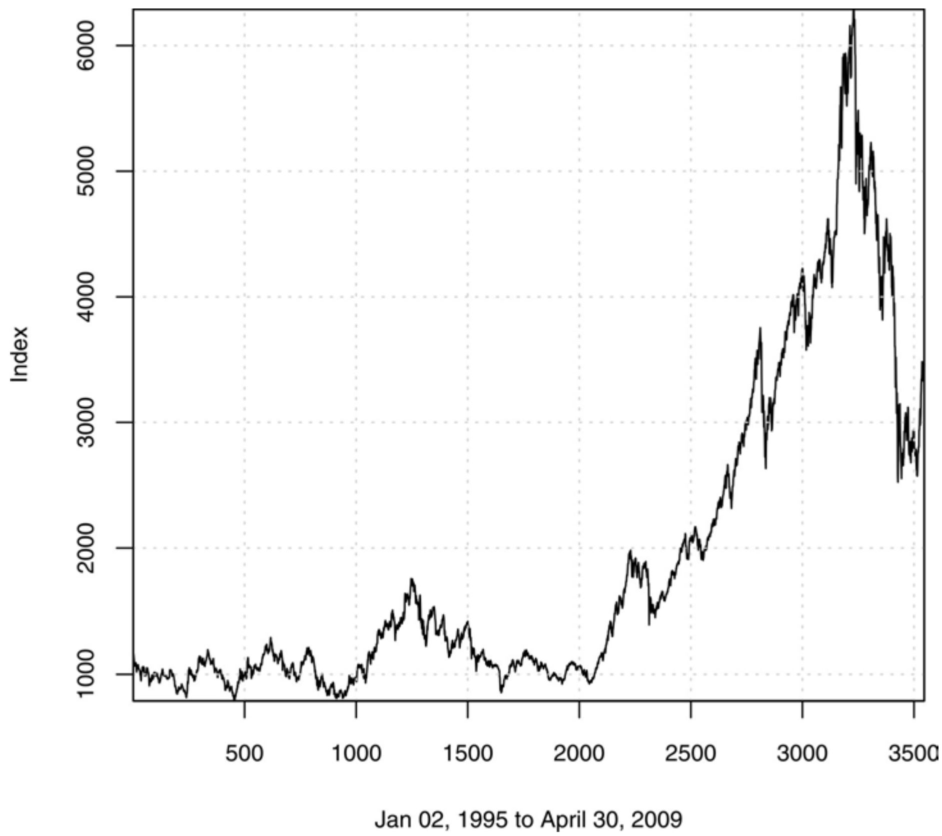

Chart 1: Time series of S&P CNX Nifty; trading days on x axis

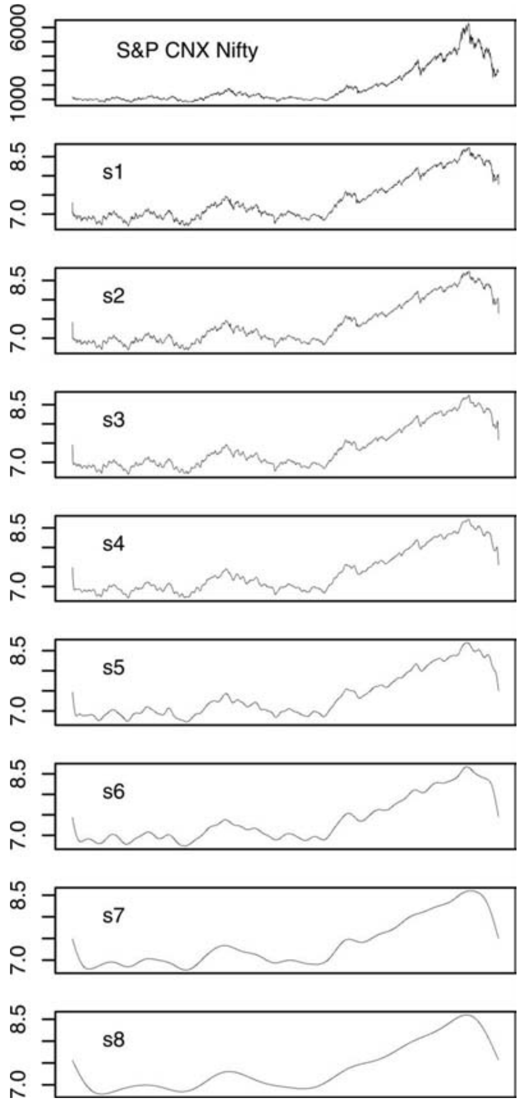

Chart 2: Decomposition levels of the S&P Nifty time series (Jan02, 1995- Apr 30, 2009), transformed with Daubchies 8 (D8) wavelet.

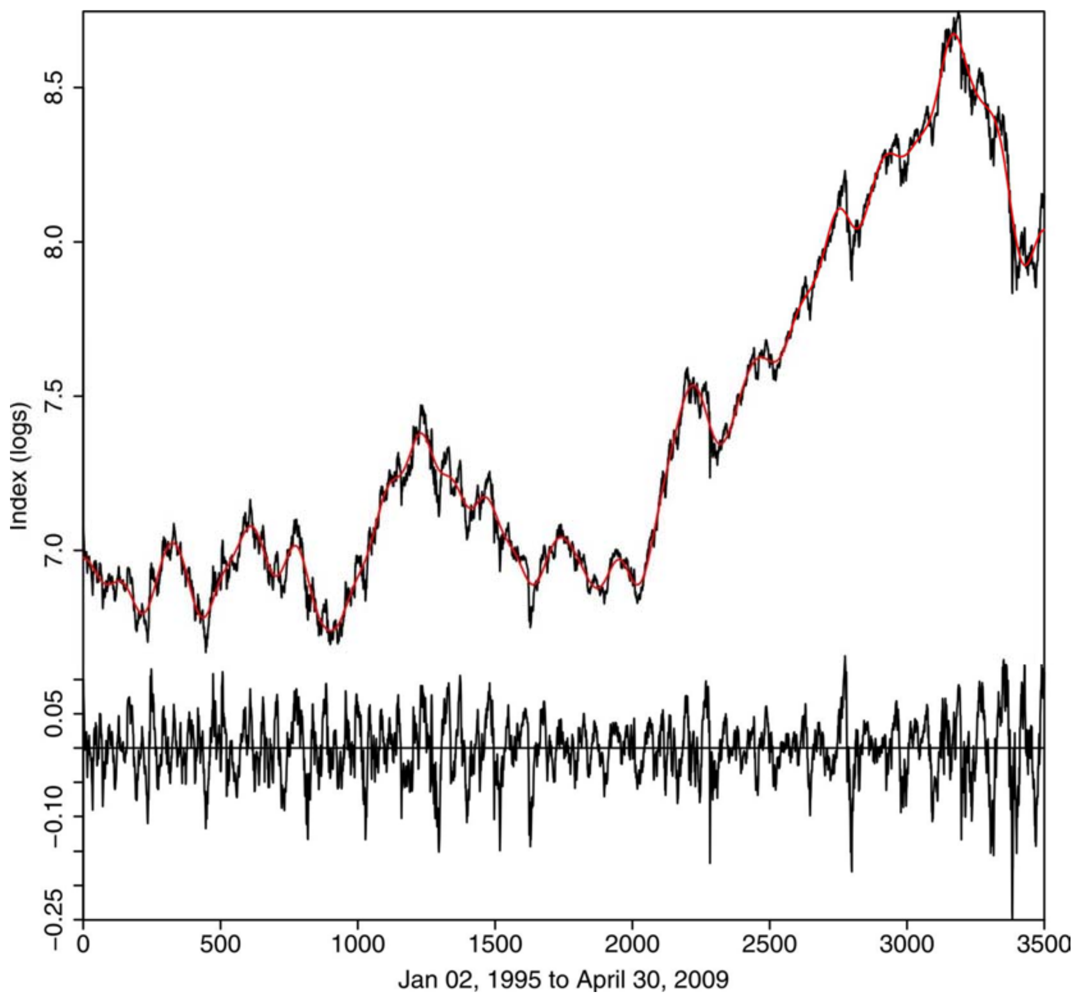

Chart 3: The underlying trend (red overlay) has been removed from the index (S&P CNX Nifty) time series using Daubchies 8 wavelet transform and reconstruction. The lower plate shows the de-trended series, which is just the fluctuation of the trend around the trend. This is not the same as a first difference.

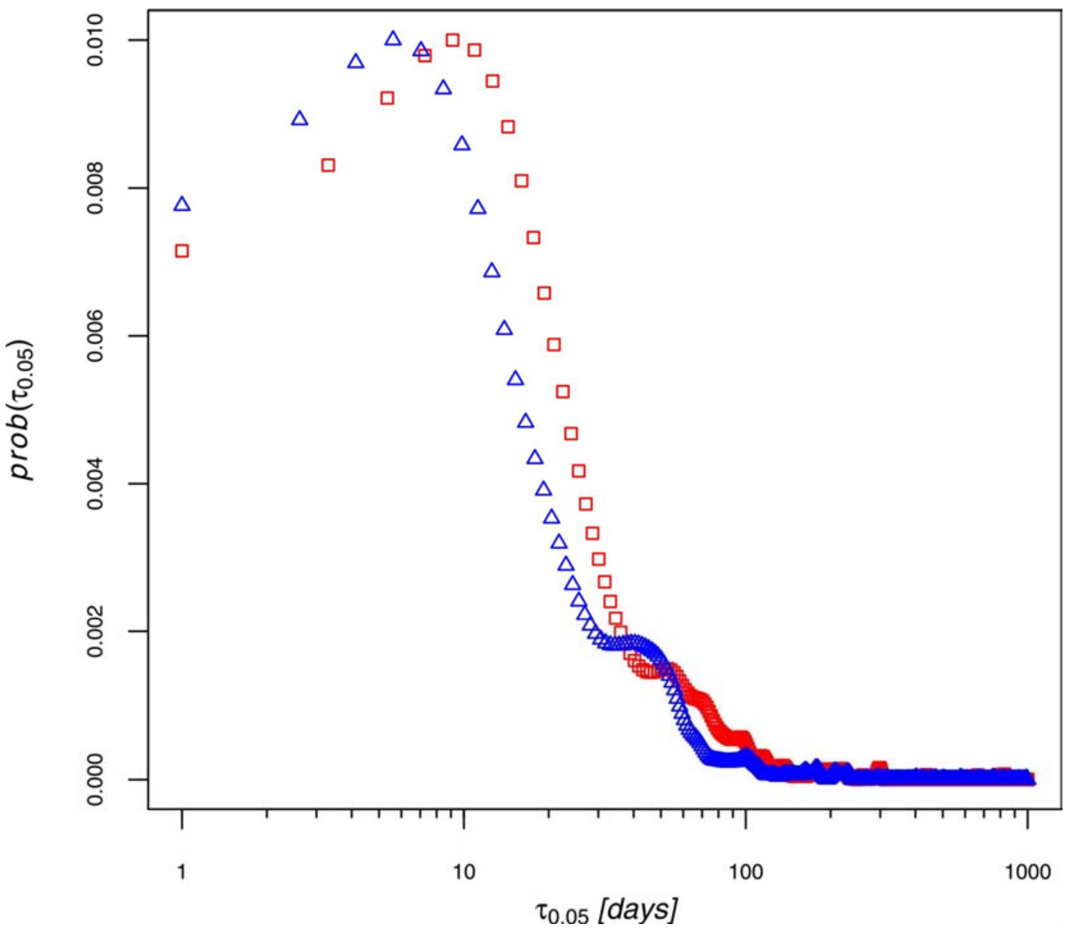

Chart 4: The probability distribution $p(\tau_{0.05})$ of the investment horizons of the S&P CNX Nifty for returns set at 5%. Squares (red, online) represent positive returns and triangles (blue, online) are for negative returns. Both distributions show a pronounced maximum and a non-zero probability for long horizons (more than 100 days).

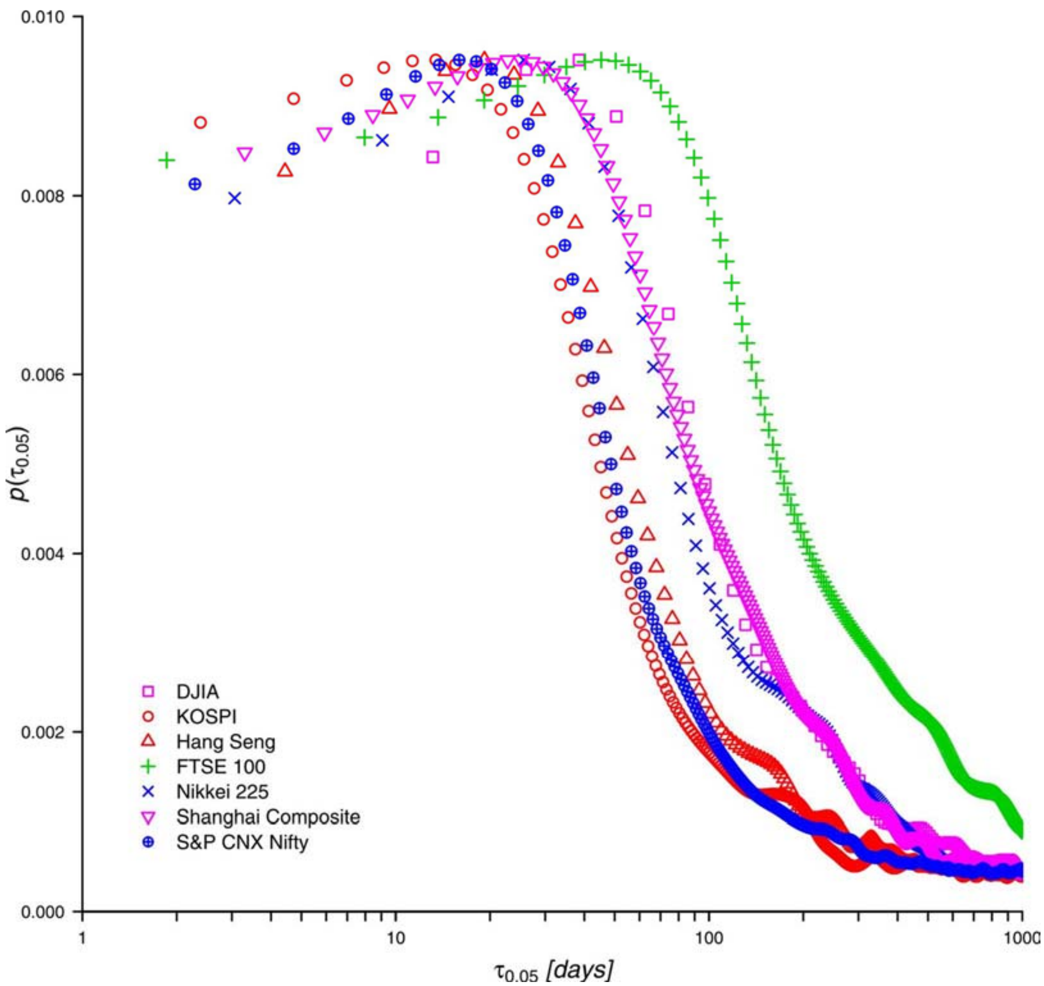

Chart 5a: The distribution of investment horizons for major stock exchanges. Note the log scale in the x axis (*Table 1 for details).*

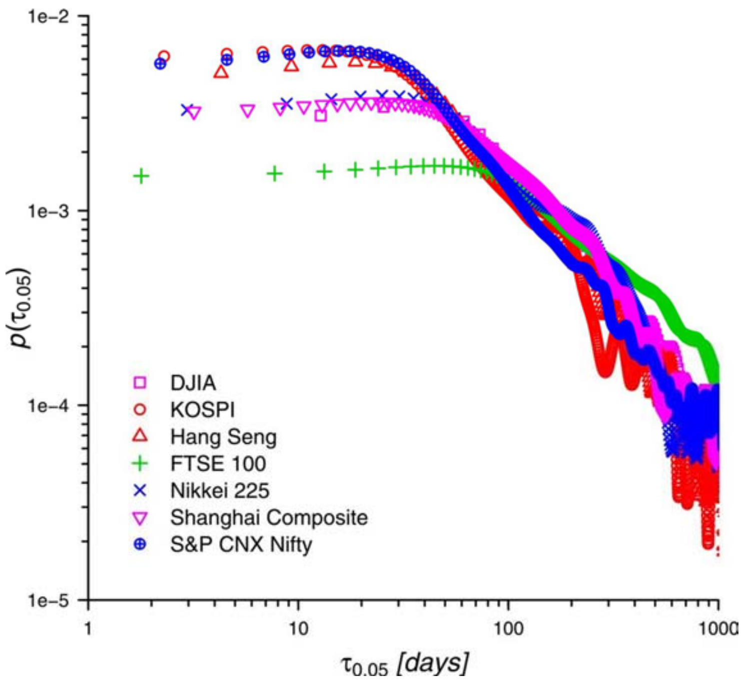

Chart 5b: The distribution of horizons on a log-log axis, which clearly shows the power law behaviour.

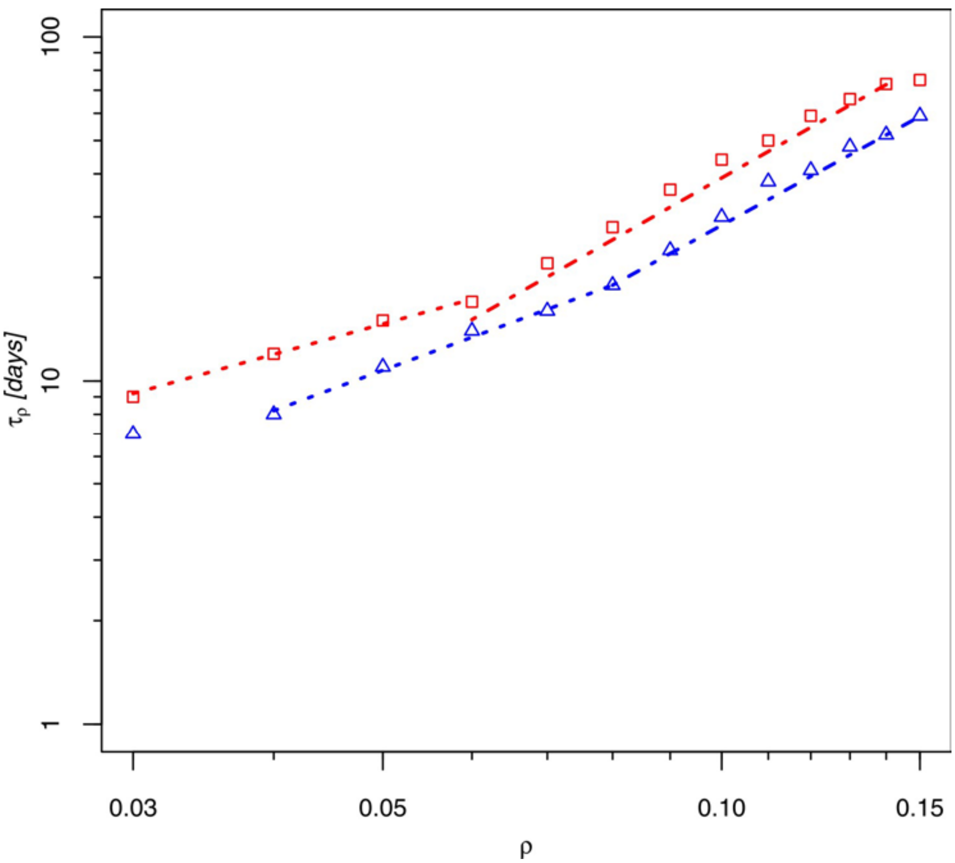

Chart 6: Optimal investment horizon of the S&P CNX Nifty as a function of the return levels. Positive returns are shown as squares (red online) and negative returns as triangles (blue online). Two regimes can be observed for both positive and negative returns, with the crossover at 6% for positive returns, and 8% for negative returns. Note the logarithmic scale on both axes.

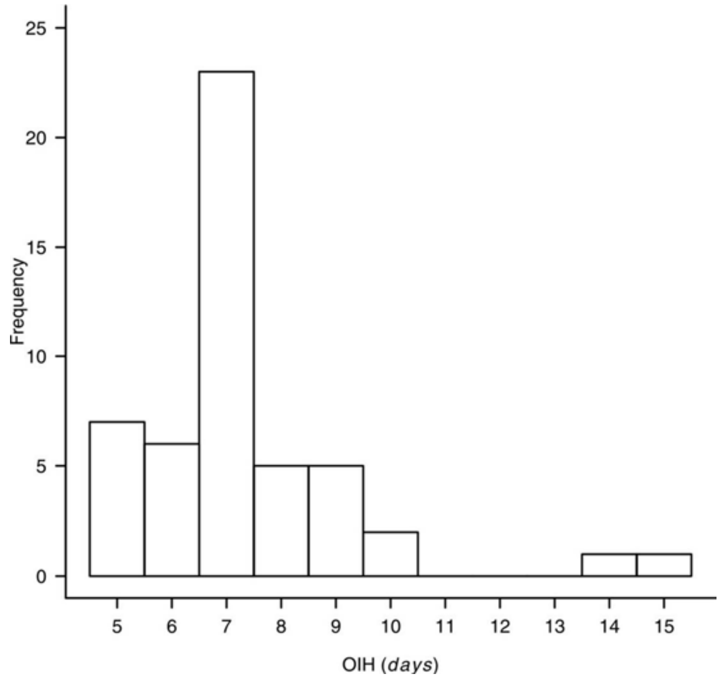

Chart 7: The frequency distribution of the optimal horizon for the 50 stocks constituting the S&P CNX Nifty for +5% returns.

Table 1: Distribution of optimal investment horizon of some major exchanges
Return level=+5%

Index	OIH (days)
DJIA	39
FTSE-100	47
Hang Seng	18
Kospi	13
Nikkei-225	25
S&P CNX Nifty	**15**
Shanghai Composite	25

Table 2: The optimal investment horizons of the constituent stocks

	Scrip name	OIH (*days*)			Scrip name	OIH (*days*)	
		+5%	-5%			+5%	-5%
1	ABB	7	8	26	TATASTEEL	7	5
2	ACC	6	6	27	UNITECH	6	4
3	REL INFRA	6	6	28	BPCL	6	7
4	CIPLA	7	7	29	BHEL	7	6
5	GRASIM	7	8	30	TATACOMM	6	6
6	AMBUJA CEM	9	7	31	WIPRO	5	6
7	HDFC	8	8	32	GAIL	7	6
8	HDFC BANK	9	8	33	ICICIBANK	7	5
9	HERO HONDA	7	6	34	AXISBANK	5	6
10	HINDALCO	7	9	35	NATIONALUM	7	5
11	HINDUNILVR	10	9	36	HCLTECH	5	6
12	INFOSYSTCH	7	6	37	BHARTIARTL	7	8
13	ITC	7	7	38	PNB	7	6
14	LT	6	7	39	MARUTI	8	7
15	M.M	7	8	40	STER	7	6
16	ONGC	7	8	41	TCS	14	9
17	RANBAXY	9	9	42	NTPC	15	10
18	RELCAPITAL	7	6	43	SUZLON	7	5
19	RELIANCE	8	7	44	RCOM	10	6
20	SAIL	5	5	45	RPL	9	8
21	SBIN	9	8	46	CAIRN	8	5
22	SIEMENS	7	6	47	IDEA	7	5
23	SUNPHARMA	7	8	48	DLF	5	4
24	TATAPOWER	8	7	49	POWERGRID	4	4
25	TATAMOTORS	7	6	50	RPOWER	4	4