Time Scales and Characteristics of Stock Markets in Different Investment Horizons

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Investors adopt varied investment strategies depending on the time scales (τ) of short-term and long-term investment time horizons (ITH). The nature of the market is very different in various investment τ. Empirical mode decomposition *(EMD)* based Hurst exponents (*H*) and normalized variance (NV) techniques have been applied to identify the τ and characteristics of the market in different time horizons. The values of *H* and NV have been estimated for the decomposed intrinsic mode functions (IMF) of the stock price. We obtained $H_1 = 0.5 \pm 0.04$ and $H_1 \geq 0.75$ for the IMFs with τ ranging from a few days to 3 months and $\tau \geq 5$ months, respectively. Based on the value of H_1, two time series have been reconstructed from the *IMFs*: a) short-term time series [$X_{ST}(t)$] with $H_1 = 0.5 \pm 0.04$ and τ from a few days to 3 months; b) long-term time series [$X_{LT}(t)$] with $H_1 \geq 0.75$ and $\tau \geq 5$ months. The $X_{ST}(t)$ and $X_{LT}(t)$ show that market dynamics is random in short-term *ITH* and correlated in long-term *ITH*. We have also found that the NV is very small in the short-term ITH and gradually increases for long-term *ITH*. The results further show that the stock prices are correlated with the fundamental variables of the company in the long-term *ITH*. The finding may help the investors to design investment and trading strategies in both short-term and long-term investment horizons.

Keywords: empirical mode decomposition, Hurst exponent, short-term investment time horizon, long-term investment time horizon, time scale, normalized variance

1. INTRODUCTION

The stock market is a complex dynamical system where the evolution of the dynamics depends on the participation of different types of investors or traders [1–3]. Investors/traders participate in the stock market to gain profit implementing different investment and trading strategies depending on investment time horizons (ITH) [4, 5]. The participation of diversified investors, reaction to the information, and short-term and long-term investment approaches play crucial roles in the movement of stock prices [4].

In the stock markets, there are mainly two types of investors: short-term investors who invest for short-term gain and long-term investors who invest for long-term gain [6, 7]. Studies show that the *ITH* for short-term investors ranges from a single day to a few months, and for long-term investors, it usually ranges from a few months to several years [8, 9]. The fund managers and foreign exchange dealers of various countries use technical analysis for the short-term *ITH* and fundamental analysis for the long-term *ITH* [8, 10]. The time scales (τ) of short-term and long-term *ITH* by the investors are generally chosen in an arbitrary manner based on the investment experience [8, 10]. So the

identification of τ from stock price time series using a well defined technique may be helpful for both the short-term and long-term investors.

As the market is mean reversing in short-term ITH [9], traders fail to generate significant returns using technical analysis [11]. On the other hand, in the long-term ITH, an investor can generate significant return or help in making decision whether to exit from that particular stock to avoid loss by determining the financial health of a company by using fundamental variables [12–14]. Fundamental analysis is an essential tool to find out the relation between stock price and fundamental variables such as book to market (B/M), sales to price, debt to equity, earnings to price, and cash flow of a stock [12–14]. The stock price is found to be positively correlated with the essential fundamental variables [14–20]. The study of the correlation in the short-term ITH and long-term ITH is essential to take a fruitful investment decision.

In the short-term ITH, the market is generally considered to be governed by psychological behavior of the investors. However, the fundamental variables are the main determining crucial factors in the long-term ITH. Usually, investors choose the τ of short-term and long-term investment horizon in an arbitrary manner [8, 9]. Recently, we used structural break study to show that the τ for the short-term is usually less than a few months [9]. The separation of the short- and long-term dynamics in terms of τ plays a vital role in the prediction of future price movement. Hence, detailed studies are required to find the correlation of the stock price with fundamental variables and to identify the τ of market dynamics in the short-term ITH and long-term ITH.

In this article, we estimated the τ of the stock price in the short-term and long-term ITH for twelve leading global stock indices and the stock price of some companies using empirical mode decomposition (EMD) based Hurst exponent (H) analysis. We have reconstructed short-term and long-term time series based on the H. Finally, we estimated the correlation coefficient between long-term time series and fundamental variables. Herein we establish that short-term ITH is normally less than 3 months and long-term ITH is more than 5 months. Correlation analysis shows that the long-term stock price is positively correlated with the fundamental variables.

The remaining part of this paper is organized as follows: In **Section 2**, we introduce the method of analysis, while **Section 3** presents the data analyzed. Results and discussion and conclusion are delineated in **Sections 4 and 5**, respectively.

2. METHOD OF ANALYSIS

A nonlinear two-step technique—EMD followed by Hilbert–Huang Transform (HHT)—has been applied to analyze the stock data as it is nonlinear and nonstationary. Nonlinearity in the stock market appears due to the presence of market frictions and transaction costs, existence of bid-ask spread, and short selling, whereas nonstationarity appears due to different time scales present in the stock market [21, 22]. This approach helps us to identify the characteristic τ and the important trends and components present in the data [3].

The EMD method decomposes the stock index and stock price into the intrinsic oscillatory modes of different τ by preserving the nonstationarity and nonlinearity of the data. These oscillatory modes are termed intrinsic mode functions (IMF). The $IMFs$ can be both amplitude and frequency modulated as well as nonstationary [23, 24]. The τ of each $IMFs$ has been identified by HHT. The HHT eliminates the spurious harmonic components generated due to the nonlinearity and nonstationarity of the data [23, 24].

The $IMFs$ satisfy the following two conditions; i) the number of extrema and the number of zero crossing must be equal or differ by one; and ii) mean values of the envelope, defined by the local maxima and local minima, for each point are zero. The IMF is calculated in the following way [23, 25]:

a. Lower envelope $U(t)$ and upper envelope $V(t)$ are drawn by connecting minima and maxima of the data, respectively, using spline fitting.
b. Mean value of the envelope $m = [U(t) + V(t)]/2$ is subtracted from the original time series to get new data set $h = X(t) - m$.
c. Repeat the processes (a) and (b) by considering h as a new data set until the IMF conditions (i and ii) are satisfied.

Once the conditions are satisfied, the process terminates, and h is stored as the first IMF. The second IMF is calculated repeating the above steps (a)–(c) from the data set $d(t) = X(t) - IMF_1$. When the final residual is monotonic in nature, the steps (a)–(c) are terminated and the original time series can be written as a set of $IMFs$ plus residue,

$$X(t) = \sum_{i=1}^{n} IMF_i + residue,$$

where IMF_i represents the ith IMF, and residue represents the trend of the stock data.

$IMFs$ are the signal with different τ. The IMF_1 is a signal with the smallest τ, the IMF_2 is the signal with the second smallest τ, and so on. Hence, EMD technique is useful to extract different τ from the signal. The characteristic τ of each IMF can be estimated from the frequency (ω) by using Hilbert Transform, which is defined as

$$Y(t) = \frac{P}{\pi} \int_{-\infty}^{\infty} \frac{IMF(t)}{t - t_I} dt,$$

where P is the Cauchy principle value, and $\tau = \frac{1}{\omega}$ where $\omega = \frac{d\theta(t)}{dt}$, and $\theta(t) = \tan^{-1}\frac{Y(t)}{IMF(t)}$ [23]. Identification of important $IMFs$ is essential to differentiate the market dynamics in short-term from long-term ITH, and the differentiation can be done by evaluating the H.

Rescaled-range (R/S) analysis is a technique to estimate the correlation present in a time series by calculating H [26–28]. Details of the R/S technique are described below. Let us consider a time series of length L and divided into p subseries of length l. Each subseries is denoted as $Y_{j,t}$, where $t = 1, 2, 3, \ldots, p$. Mean and standard deviation of the subseries $Y_{j,t}$ are defined as

$$D_t = \frac{1}{l} \sum_{j=1}^{l} Y_{j,t}$$

and

$$S_t = \sqrt{\frac{1}{l} \sum_{j=1}^{l} \left(Y_{j,t} - D_t \right)^2},$$

respectively. Mean adjusted series is calculated as

$$Z_{j,t} = Y_{j,t} - D_t$$

for $j = 1, 2, 3, \ldots, l$. Cumulative time series is given by

$$X_{j,t} = \sum_{i=1}^{j} Z_{i,t}$$

for $j = 1, 2, 3, \ldots, l$.

Range of the series has been calculated as

$$R_t = \max \left(X_{1,t}, \ldots, X_{l,t} \right) - \min \left(X_{1,t}, \ldots, X_{l,t} \right).$$

Individual subseries range can be rescaled or normalized by dividing the standard deviation. So, R/S is written as

$$(R/S)_l = \frac{1}{p} \sum_{t=1}^{p} R_t \big/ S_t.$$

The ratio of each subseries of length l is expressed as $(R/S)_l \propto l^H$, where H is the Hurst exponent. H can be estimated from the slope of $\ln(R/S)$ vs. $\ln(l)$. For a random time series, H is around 0.5, and for correlated and anticorrelated time series, H is greater than 0.5 and less than 0.5, respectively.

Normalized variance (NV) is another important statistical tool to identify the important $IMFs$ based on the energy of the signal. The higher the NV value is, more significant the signal is. The technique estimates the energy of the ith $IMFs$ by calculating variance [29, 30], and NV of ith IMF is defined as

$$NV_i = \frac{\sqrt{\sum_t IMF_i^2(t)}}{\sum_{i=1}^{q} \sqrt{\sum_t IMF_i^2(t)}},$$

where q is the total number of IMF.

3. DATA ANALYZED

We have analyzed the stock indices and stock prices of a few companies of different countries from December 1995 to July 2018, namely, 1) S&P 500 (USA), 2) Nikkei 225 (Japan), 3) CAC 40 (France), 4) IBEX 35 (Spain) 5) HSI (Hong Kong), 6) SSE (China), 7) BSE SENSEX (India), 8) IBOVESPA (Brazil), 9) BEL 20 (Euro-Next Brussels), 10) IPC (Mexico), 11) Russell 2000 (USA), and 12) TA125 (Israel), and stock prices of the companies 1) IBM (USA), 2) Microsoft (USA), 3) Tata Motors (India), 4) Reliance Communication (RCOM) (India),

5) Apple Inc. (USA), and 6) Reliance Industries Limited (RIL) (India). Stock indices and price data were downloaded from yahoo finance, and the analysis was carried out using MATLAB software.

4. RESULTS AND DISCUSSIONS

The stock market shows different behavior in different investment horizon. EMD based H and NV techniques have been applied to analyze the market dynamics as discussed below.

Figures 1A–J show the IMF_1 to IMF_9 and the residue of the S&P 500 index calculated using EMD technique as described in detail in **Section 2**. IMF_1 in **Figure 1A** represents the mode with the lowest τ, and it gradually increases with the increase in IMF numbers. **Figure 1J** represents the residue of the signal, which indicates the overall trend of the index. Similarly, we have calculated all $IMFs$ for all the indices and companies to analyze the market.

4.1. *EMD* Based *H* and *NV* Analysis

H has been calculated for all the $IMFs$. **Figure 2A** shows the typical plot of H versus τ of all the indices and companies. We obtained single H from $IMF_1 - IMF_5$ and it is indicated as H_1. Higher-order IMF shows two H, namely, H_1 and H_2. We obtained $H_1 \approx 0.5 \pm 0.04$ for IMF_1 to IMF_5 with τ ranging from a few days (D) to 3 months (M). The value of H_1 jumps to ≥ 0.75 for IMF_6 with $\tau \approx 5\ M$. It gradually increases for IMF_7 to IMF_9 with a τ ranging from 1 year (Y) to 12 Y. $H_1 \approx 0.5 \pm 0.04$ for IMF_1 to IMF_5 indicates that the nature of the first five $IMFs$ is random. IMF_6 to IMF_9 show a long-range correlation up to one period lag. τ of IMF_1, IMF_2, IMF_3, IMF_4, and IMF_5 of all the indices and companies stock data analyzed here are in the range of 3–4 D, 7–10 D, 15–18 D, 1–1.5 M, and 2.5–3 M, respectively.
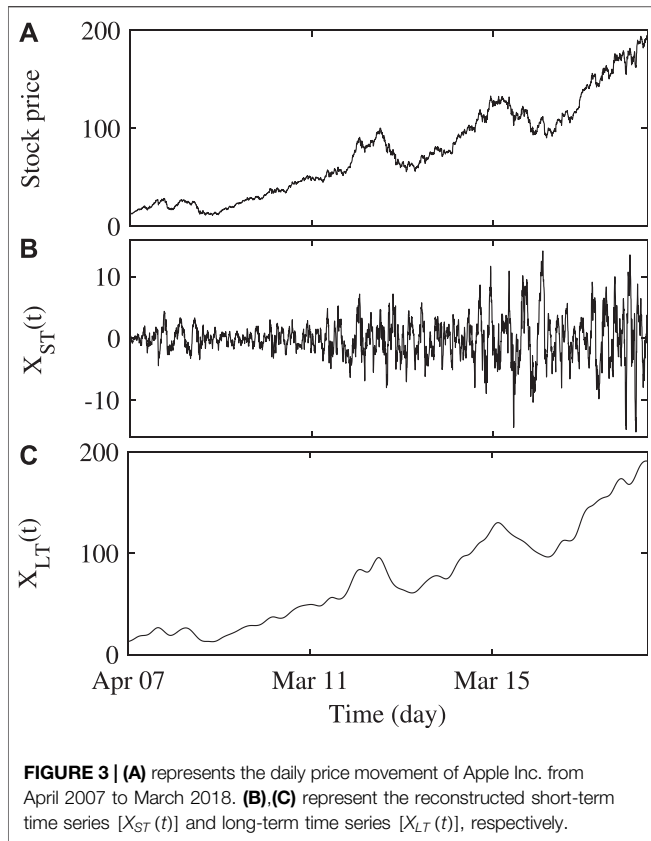
To further validate the robustness of the proposed method, analysis of the decomposed time series has been carried out using NV technique. **Figures 2B–D** represent NV of all the $IMFs$ of all the indices and companies, where plots have been arranged according to the order of higher NV of $IMFs$. **Figures 2B–D** show that the value of NV is very low for all the indices and companies up to IMF_5, and NV increases significantly for IMF_6 to IMF_9. Hence, based on the value of NV the time series can also be decomposed into two time series with two distinct time horizons: short-term time series by adding IMF_1 to IMF_5 and long-term time series by adding IMF_6 to IMF_9 plus residue as described in **Section 4.2**. Further, NV technique can be used to find a time series with important time scale in the form of IMF. **Figures 2B–D** show that the value of NV is higher for IMF_7 with $0.8\ Y \leq \tau \leq 1.9\ Y$, IMF_8 with $2.0\ Y \leq \tau \leq 4.4\ Y$, and IMF_9 with $4.5\ Y \leq \tau \leq 12\ Y$, respectively, for the companies mentioned in the plots. The decomposed time series with higher value of NV may play important role to predict long-term behavior of the market [29]. More such studies in detail can be pursued in future.
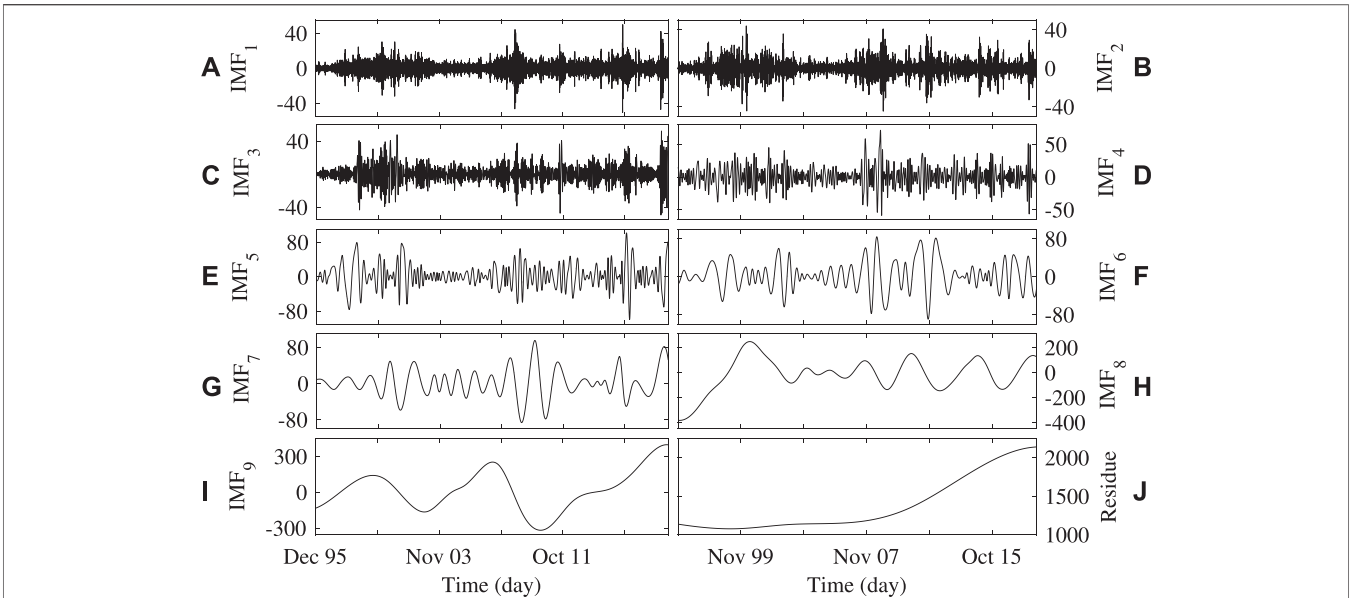
FIGURE 1 | The plots **(A)–(I)** represent the IMF_1 to IMF_9, respectively, and **(J)** represents residue of the S&P 500 index.
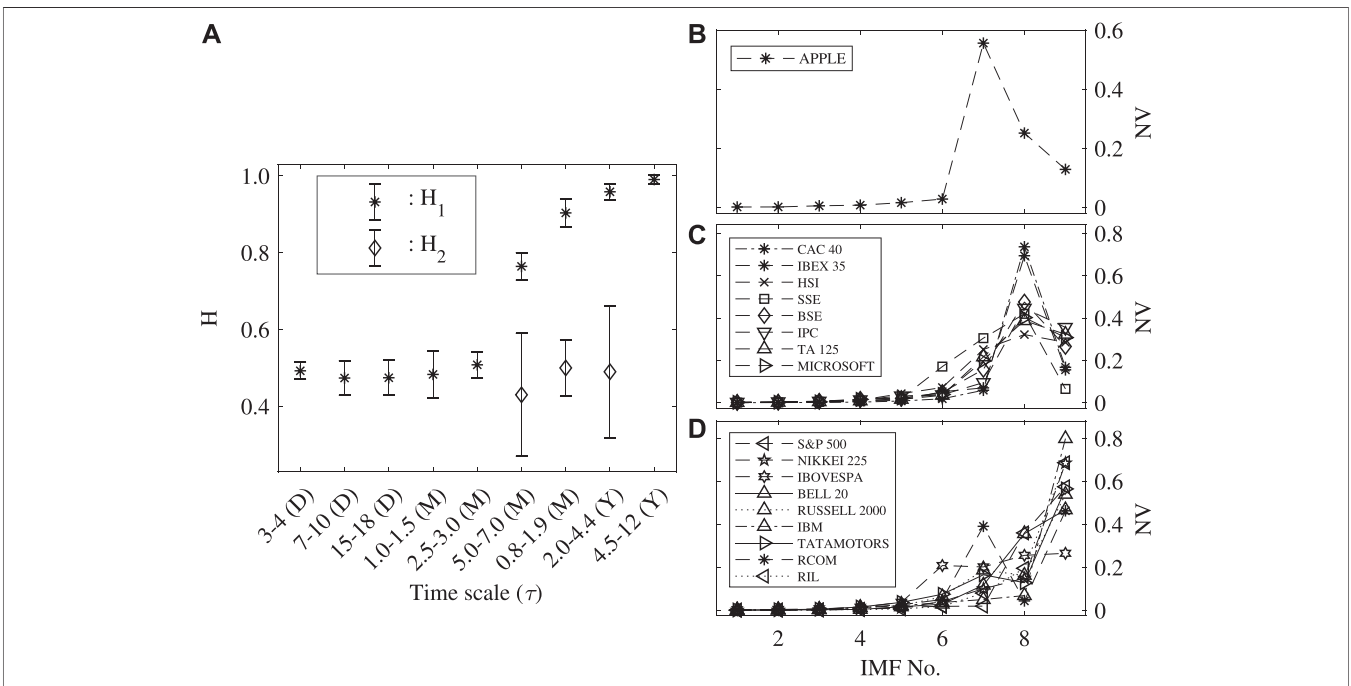
FIGURE 2 | (A) shows the Hurst exponents (H_1 and H_2) vs. τ of all the $IMFs$ of all the indices and companies with 2σ error bar. The first point represents the average value of H_1 of all the first $IMFs$ of all stock data, the second point represents the average value of H_1 of all the second $IMFs$ of all stock data, and so on. For IMF_1 to IMF_5 of all indices and companies $H_1 = 0.5 \pm 0.04$ with a maximum τ of around 3 M. The value of H_1 jumps to 0.75 ± 0.04 for IMF_6 (with a $\tau \approx 5\,M$) and gradually increases for IMF_7 to IMF_9. H_1 value shows that nature of IMF_1 to IMF_5 is random and IMF_6 to IMF_9 have a long-range correlation. (D), (M), and (Y) in the x-axis represent the day, month, and year, respectively. **(B)–(D)** represent the normalized variance (NV) of $IMFs$ of all the indices and company, respectively.

FIGURE 3 | (A) represents the daily price movement of Apple Inc. from April 2007 to March 2018. **(B),(C)** represent the reconstructed short-term time series $[X_{ST}(t)]$ and long-term time series $[X_{LT}(t)]$, respectively.

4.2. Reconstruction of Short-Term and Long-Term Time Series

In order to analyze the market dynamics in short-term *ITH* and long-term *ITH*, we have reconstructed two time series from the decomposed *IMFs* as discussed below.

We have reconstructed a time series $[X_{ST}(t)]$ by adding the IMF_1 to IMF_5 whose $H_1 \approx 0.5 \pm 0.04$, that is, $X_{ST}(t) = \sum_{i=1}^{5} IMF_i$. The time scale of $X_{ST}(t)$ ranges in $3\,D \leq \tau \leq 3\,M$. **Figure 3B** shows the reconstructed time series $X_{ST}(t)$ obtained by decomposing the original time series of Apple Inc. which is shown in **Figure 3A**. $H_1 \approx 0.5 \pm 0.04$ shows that the stock market is random when τ ranging from a few days to 3 months. Hence, $X_{ST}(t)$ represents the short-term time series in $3\,D \leq \tau \leq 3\,M$. The above analysis shows that the market behavior is random in the short-term *ITH* when τ is in the range of a few days to 3 months.

Higher-order *IMF* shows two Hurst exponents (H_1 and H_2). We have reconstructed another time series $[X_{LT}(t)]$ by adding IMF_6 to IMF_9 whose $H_1 \geq 0.75$ and residue, that is, $X_{LT}(t) = \sum_{i=6}^{9} IMF_i +$ residue to understand the market dynamics in long-term *ITH*. The time scales of $X_{LT}(t)$ are $\geq 5\,M$. **Figure 3C** shows the reconstructed long-term time series $[X_{LT}(t)]$ obtained by decomposing the original time series of Apple Inc., which is shown in **Figure 3A**. The present analysis yielded a H_1 value of ≥ 0.75, which shows that the stock market has a long-range correlation with $\tau \geq 5\,M$. Hence, $X_{LT}(t)$ represents the long-term time series with $\tau \geq 5\,M$. From the above analysis, it can be

concluded that the market has a long-range correlation in the long-term *ITH* with $\tau \geq 5\,M$ and hence may be used to predict a future price. Further, it has been observed that the future price of a stock is actually much more dependent on the fundamental variables of a company. In order to understand such dependence, we have studied the correlation between $X_{LT}(t)$ and the fundamental variables of the companies.

Table 1 shows that the correlation coefficient (J) between $X_{LT}(t)$ and three fundamental variables: sale, net profit (NP), and cash from operating activity (COA) for some Indian and American companies which are listed in NSE, NYSE, and NASDAQ, from March 2007 to March 2018 in the annual price level. Fundamental variables data have been downloaded from screener and macrotrends. We obtained a positive correlation between $X_{LT}(t)$ and sale, NP, and COA for all the years. It implies that stock price is correlated with the sale, NP, and COA. We have obtained a small J for a few stocks. These stocks show a small J for the following two possible reasons: a) the stock price of a company with strong growth prospect increases even though sale or NP decreases temporarily; b) the stock price of a company with weak growth prospect decreases even though sale or NP increases temporarily. Hence, for long-term investment, the fundamental variables are the most crucial variables for the prediction of the future price. In the future, we would like to study the correlation between stock price and other fundamental variables of companies.

5. CONCLUSION

In this paper, we have studied the stock market using the empirical mode decomposition (*EMD*) based Hurst exponent (*H*) analysis and normalized variance (*NV*) technique. *EMD*

TABLE 1 | Correlation coefficient (J) between reconstructed long-term time series $[X_{LT}(t)]$ and three fundamental variables of some Indian and American companies.

Company	Sale	NP	COA
NSE: ASIANPAINT	0.9930	1.0000	0.9441
NSE: BPCL	0.6923	0.8322	0.6853
NSE: CIPLA	0.8951	0.6713	0.6713
NSE: DRREDDY	0.9441	0.8671	0.9510
NSE: EICHERMOT	0.9441	0.9790	0.9860
NSE: GAIL	0.5664	0.5804	0.5804
NSE: GRASIM	0.8462	0.4615	0.4615
NSE: HCLTECH	0.9441	0.9231	0.8951
NSE: HEROMOTOCO	0.9650	0.9580	0.9021
NSE: HINDALCO	0.2587	0.4545	0.3776
NSE: HINDUNILVR	0.9720	0.9860	0.8252
NSE: TATAMOTORS	0.8462	0.7832	0.9091
NSE: RCOM	0.0490	0.9510	0.5035
NSE: RELIANCE	0.1119	0.7203	0.4476
NYSE: JNJ	0.8352	0.2747	0.8022
NASDAQ: AMZN	0.9890	0.4231	0.9890
NASDAQ: GOOGL	0.9231	0.8462	0.9231
NASDAQ: AAPL	0.9615	0.9396	0.9341
NASDAQ: MSFT	0.7253	0.0659	0.6484
NASDAQ: INTC	0.9011	0.5879	0.8681

First column: Sale, second column: NP, and third column: COA.

technique has been applied to decompose the time series in the form of IMF. H and NV have been calculated for all the IMF to understand the nature of the market dynamics.

The analysis yielded a value of $H_1 = 0.5 \pm 0.04$ for IMF_1 to IMF_5. A short-term time series $[X_{ST}(t)]$ is reconstructed by adding IMF_1 to IMF_5. The time scale of $X_{ST}(t)$ ranges from a few days to 3 months. The estimated value of $H_1 = 0.5 \pm 0.04$ which shows that the stock market is random in the short-term ITH. We have estimated the value of $H_1 = 0.75 \pm 0.04$, $H_1 = 0.90 \pm 0.04$, $H_1 = 0.96 \pm 0.02$, and $H_1 = 0.99 \pm 0.02$ for IMF_6, IMF_7, IMF_8, and IMF_9, respectively, for all the data. $H_1 > 0.5$ shows that the IMF_6 to IMF_9 have long-range correlation, and hence a long-term time series $[X_{LT}(t)]$ is reconstructed by adding IMF_6 to IMF_9 and residue. The time scale of $X_{LT}(t)$ is greater than 5 months. The results show that the market is random with $\tau \leq 3\,M$ and having a long-range correlation with $\tau \geq 5\,M$. The study of the correlation between $X_{LT}(t)$ and sale, net profit, and cash from operating activity of different companies shows that the market is positively correlated with the fundamental variables of a company in long-term ITH. Hence, the dynamics of the market may be predicted in long-term ITH using fundamental variables.

A detailed study of the market in the long-term ITH in terms of fundamental variables of a company is necessary to predict the future price. We believe that the outcome of the present study may help in making investment decisions in both short-term ITH and long-term ITH.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. These data can be found here: https://in.finance.yahoo.com, https://www.screener.in, https://www.macrotrends.net

AUTHOR CONTRIBUTIONS

All the authors have equally contributed to preparing the manuscript.

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