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Hurst Exponent Anaysis of Indian Stock Market: Case of Covid19

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ABSTRACT

This study assesses how the Corona virus pandemic (COVID-19) affected the Indian Stock market by analyzing its market efficiency and predictability using a concept borrowed from physics and widely applied to financial time series . Nifty 50 and 14 Nifty Sectoral indices are analysed using the Hurst Exponent .The Closing prices of Nifty 50 and 14 sectoral indices listed on NSE ranging from November 1, 2017 to January 24, 2020 (Pre- Covid) and January 27, 2020 to March 11, 2022 (during Covid)are utilized for this study . The findings are interesting as Hurst Exponent is found to be greater than 0.5 most of the times for all the series. This implies stock market persistency in 'Pre Covid' as well as 'during Covid' phase for the Nifty indices except Nifty Bank index , Nifty Financial Services index and Nifty Private Bank index . These findings are suggestive of high predictability in Indian stock market irrespective of the economic phase of the economy. This study also opens avenues for further research . Was persistency ,and hence predictability, only a feature of emerging economies during Covid19 or was it a world wide phenomena ? Is'Random Walk Theory' not applicable in Indian Stock market?

Keywords: Hurst Exponent , Rescaled Range , Nifty 50 , Sectoral Indices , Persistence , COVID 19

1.0 INTRODUCTION

The benefits of global level integration are also accompanied by its flaws. Any news announced at a corner of the world leads to its impact on another corner. This is studied through the concept of EMH (Efficient Market Hypothesis) which helps to measure the level of Market efficiency. Efficiency means all accessible information about security is mirrored into its price, so it's apparent that no one can beat the market via predicting the future prices. Theory that delivered and elaborated this concept of efficiency is known as Efficient Market Hypothesis introduced by Fama (1970). EMH suggest that security prices are always at their truthful price in the market, therefore there is no threat to buy undervalued security and sell overvalued security to outperform the market. In short, trend analysis is of no use. Security prices will constantly be displaying a random walk.

The Covid-19 Virus originated in December 2019 from Wuhan, China, one of the greatest economies in the world had created a disastrous pandemic across the globe which affected deeply the whole economies in the world. Emergency lockdowns, financial problems faced by the people and government of the world-wide countries created situation of panic and distress among them and also the market abnormality. It crashed the world economy including stock market, crude oil prices, foreign exchange market etc.

The present study investigates long term predictability of time series data of Indian stock market using the Hurst exponent during the time of this pandemic to analyze its deep impact on this market. For the same, the data includes daily returns of closing values of Nifty 50 and Nifty sectoral Indices from November 1, 2017 to January 24, 2020 (Pre- Covid) and January 27, 2020 to March 11, 2022 (During Covid).

2.0. LITERATURE REVIEW

Virgilijus Sakalauskasn and Dalia Kriksciuniene (2012) used aggregated indicators, specifically the aggregated entropy-based (EB) indicator, for forecasting reversal points in the long-term trend direction of financial data series. The study focuses on the NASDAQ OMX Vilnius stock exchange (OMXV) index from 2004-03-18 to 2009-07-30. They found that the market exhibited low efficiency during the analyzed period, typical for emerging markets, as indicated by Shannon's entropy. The Hurst exponent analysis suggested that the OMXV index tended to be persistent, deviating from the efficient market hypothesis. By combining the Hurst exponent and Shannon's entropy into the aggregated EB indicator, they aimed to improve prediction accuracy for long-term trend reversal points. They utilized a neural network to forecast these reversal points and observed that when the declining EB value crossed the 0.5 threshold, the reversal of the long-term trend in the OMXV index followed soon after.

M Karamchandani, S Mohadikar, and S Jain (2014) investigated non-linear dynamics and volatility in major stock indices of BRIC economies using tools from Econophysics. Hurst Exponent analysis suggests predictability in Russian, Indian, and Chinese markets, with the Indian market being the least volatile. Sensex demonstrates efficiency with high returns and low risk. The findings offer insights for investors, policymakers, and regulators, indicating potential trends, market entry/exit points, and policy interventions. Shannon Entropy analysis confirms the volatility rankings. Overall, integrating Econophysics tools enhances understanding and decision-making in financial markets, potentially leading to increased efficiency and better forecasting.

SR Bentes and R Menezes(2012) examined stock market volatility using entropy as an alternative to the standard deviation. Data from seven indexes, including CAC 40, MIB 30, NIKKEI 225, PSI 20, IBEX 35, FTSE 100, and SP 500, were analyzed. The results suggest that entropy, especially Shannon entropy, offers advantages over the standard deviation, capturing uncertainty without assuming specific probability distributions. Specifically, the CAC 40 and NIKKEI 225 indexes consistently exhibited the highest volatility levels. For instance, Shannon entropy results ranged from approximately 1.25 to 1.40 for different indexes, indicating significant differences in volatility levels.

M Sheraz, S Dedu, V Preda (2015) explored entropy measures as a tool for assessing volatility in stock markets, focusing on the Shannon, Tsallis, Rényi, and approximate entropies. Weekly and monthly data from four stock indices (CAC 40, Hang-Seng, FTSCST China, and FTSE.MI) from 2000 to 2012 were analyzed. Shannon entropy, computed using various estimators, highlighted the volatility differences among the indices. The results indicated that the Paris Index exhibited higher volatility compared to others, especially evident in the approximate entropy values. Overall, the entropic approach offers a new perspective on understanding stock market volatility, with potential implications for future research in the field.

L Ponta, A Carbone (2018) implemented a Shannon entropy-based measure on the time series of prices and volatilities from six financial markets over six years. It finds that the entropy of price series is practically invariant across markets, while volatility entropy varies by market. A Market Heterogeneity Index is derived from the entropy measure, providing a smoother evaluation of portfolio composition compared to the Sharpe ratio. The Shannon entropy quantifies the information content, intimately linked to technical traders' viewpoints.

S Patra, GS Hiremath (2022) utilized Shannon entropy to measure the dynamic efficiency of stock markets across various regions from 1994 to 2017. It finds that stock market efficiency evolves and is influenced by global, regional, and domestic economic factors. Emerging markets have improved efficiency through financial liberalization but are susceptible to global shocks. The study identifies periods of increased efficiency associated with economic reforms and trading infrastructure improvements. However, financial crises and global events lead to troughs in efficiency. The findings highlight the importance of an adaptive market framework, active portfolio management, and the presence of abnormal returns. Overall, the study suggests that stock market efficiency is complex and time-varying, requiring investors to adapt quickly to capitalize on opportunities.

A Chaudhuri; S Mukherjee; S Chowdhury; B Sadhukhan; R T Goswami (2018) investigated the fractality and stationarity of the average Sensex values of the Bombay Stock Exchange (BSE) and the American Stock Exchange NASDAQ between October 31, 2007, and November 1, 2017. They employed statistical techniques like General Hurst Estimation (GHE) and Higuchi’s Fractal Dimension (HFD) to compute the Hurst Exponent for the time series. The results indicate that both BSE and NASDAQ exhibit Short Range Dependent (SRD) anti-persistent behavior, suggesting that their future values tend to return to their long-term mean. The Hurst exponent values for both time series are below 0.5, confirming their non-linear dynamics. The findings suggest that BSE and NASDAQ are complex and non-linear processes rather than random trends, with NASDAQ exhibiting greater stability than BSE. Further research is recommended to explore the non-linear dynamics of these stock markets.

3.0 OBJECTIVES

The main objective of the paper is to study existence of predictability in Indian Stock Market . The Indian stock market can be studied as a whole by studying broad based equity index and also at sectoral level. There are 14 sectoral indices listed on NSE .This study tries to accomplish a comprehensive analysis of the Indian stock market by studying existence of predictability in Nifty 50 Index and the 14 Nifty Sectoral Indices by Hurst Exponent analysis. Furthermore

4.0 METHODOLOGY

Closing prices of Nifty 50 and 14 sectoral indices listed on NSE ranging from November 1, 2017 to January 24, 2020 (Pre- Covid) and January 27, 2020 to March 11, 2022 (During Covid) are used for this study. The daily closing prices for all the 15 indices were converted into return series.

Further, the rescaled range method is used for calculation of Hurst exponent. Its purpose is to provide an assessment of how the apparent variability of a series changes with the length of the time period being considered.

To estimate the Hurst exponent, first an estimate of the dependence of the rescaled range on the time span n of observations is calculated. A time series of full-length N is divided into a number of shorter time series of length n =N, N/2, N/4, …… The average rescaled range is then calculated for each value of n.

R/S analysis can be calculated by following steps. Firstly, the mean value m is calculated:

$m = \frac{1}{n}\sum_{i=1}^{n} X_i$ …………………………………………………………………. eq 1

Where,

X_i is the daily return series of Index under study

After this, a mean adjusted return series Y_t is generated:

$Y_t = X_t - m$ ………………………………………………………………………. eq 2

Where,

t= 1,2, ……., n

then, the cumulative deviation series Z is calculated:

$Z_t = \sum_{i=1}^{t} Y_i$ ……………………………………………………………………eq 3

Where,

t= 1,2, ……., n

Further, the range series R is calculated-

R_t =max $(Z_1, Z_2,\ldots, Z_t)-$ min$(Z_1, Z_2,\ldots, Z_t)$ ……………………………………………eq 4

t= 1,2, ……., n

Next, the standard deviation series S is calculated:

S_t is the Standard deviation of the return series.

$s_t = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(X_i - m)^2}$ …………………………………………………………………eq 5

Finally, the rescaled range analysis (R/S) can be estimated.

$(R/S)_t = R_t/S_t$, ………………………………………………………………………eq 6

And it is averaged over all the partial time series of length n to get E(R/S), that is estimated Rescaled Range.

Hurst found that R/S actually scales by power law and he formulated the following relationship:

$E(R/S) = C*n^H$ ………………………………………………………………………...eq 7

Where,

R/S = Rescaled range

C= Constant, and

H= Hurst Exponent

n = number of observations

Further the hurst is calculated with the following regression equation:

$\text{Log } (R/S)_n = \text{Log } C + H \text{ Log } n$ ………………………………………………………eq 8

Here, $\text{Log } (R/S)_n$ is regressed with Log n using linear least squares method and the slope so obtained is the Hurst Exponent. The values of the Hurst Exponent range between 0 and 1.

Hurst Value is more than 0.5

If the Hurst is more than 0.5 then it would indicate a persistent time series (roughly translates to a trending market).

Hurst Value is less than 0.5

If the Hurst Value is less than 0.5 then it can be considered as an anti-persistent time series (roughly translates to sideways market).

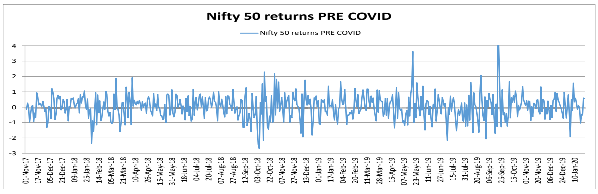
Hurst Value is 0.5

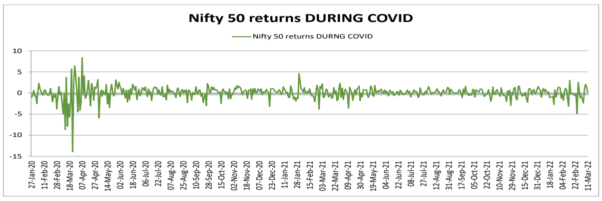
If the Hurst value is 0.5 then it would indicate a random walk or a market where prediction of future based on past data is not possible.

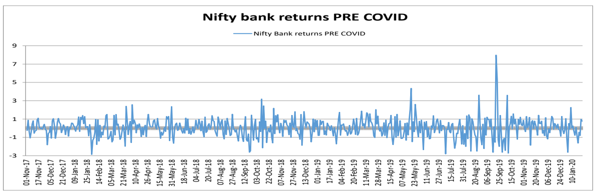
5.0 FINDINGS AND DISCUSSION:

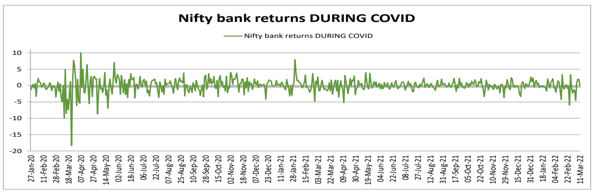
The daily closing prices for all the 15 indices were converted into return series and thereafter descriptive statistics were completed on the pre COVID 19 return series and during COVID 19 return series as well.

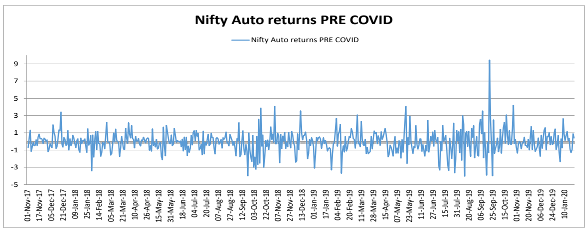
Graphs of Nifty 50 & 14 Sectoral indices returns for pre Covid(1/11/17 to 24 /1/20) and during Covid phase (27/1/20 to 11/3/22)

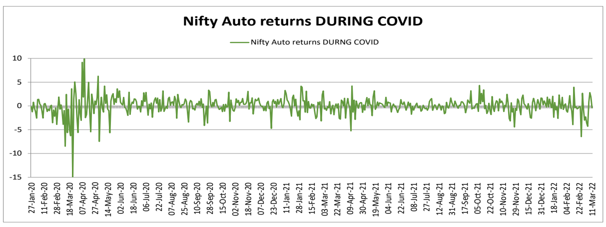












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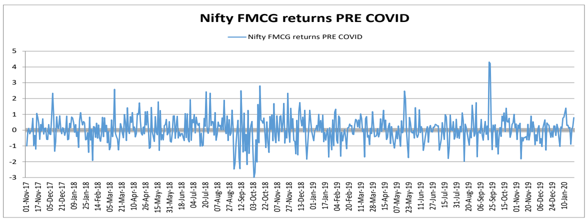

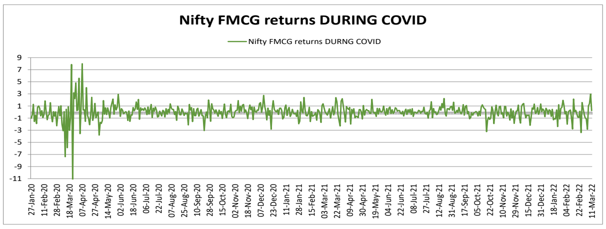

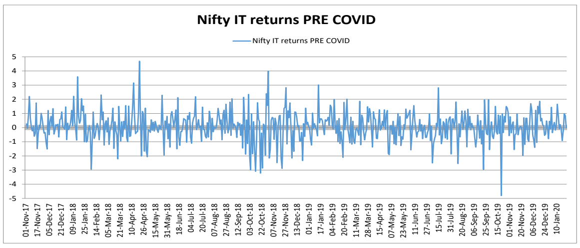

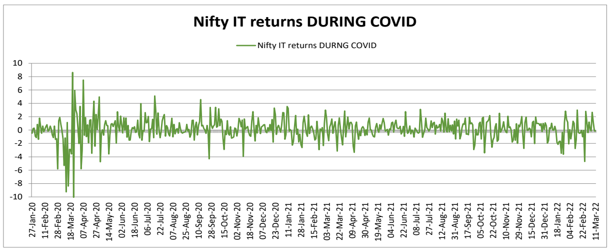

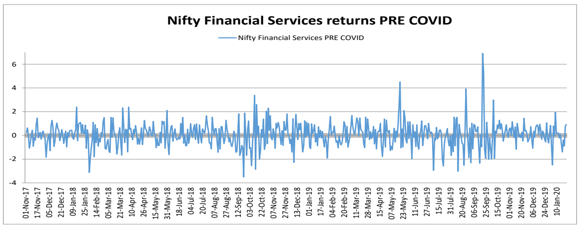

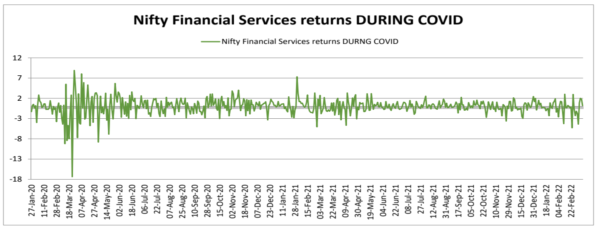

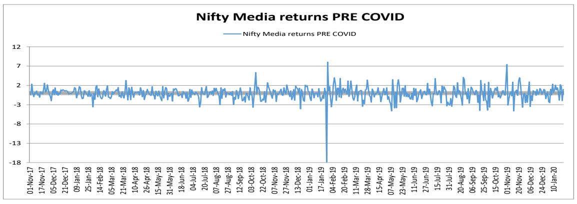

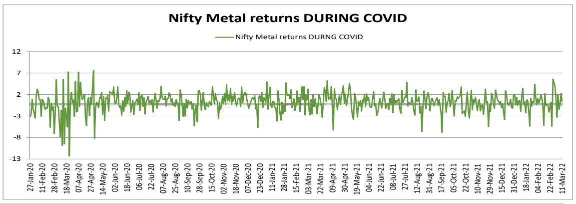

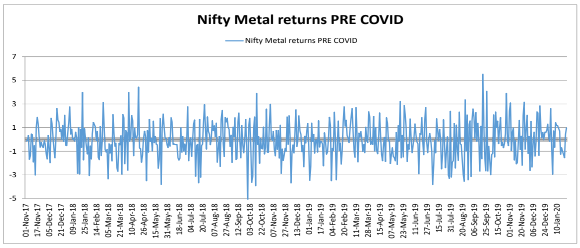

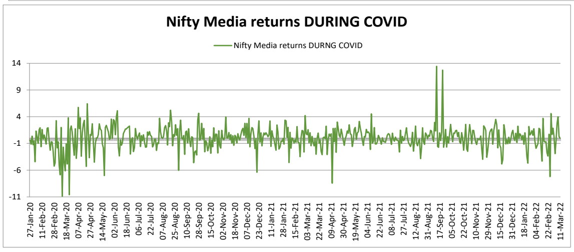

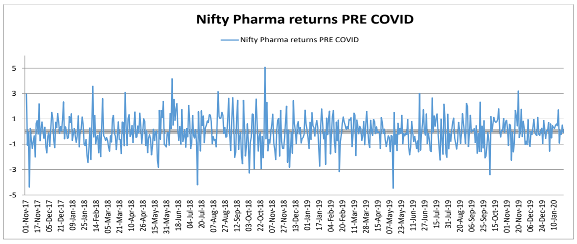

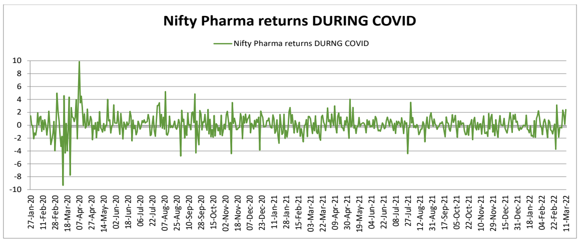

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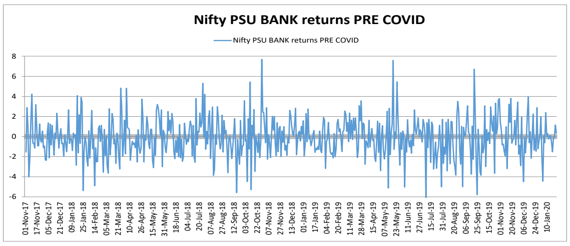

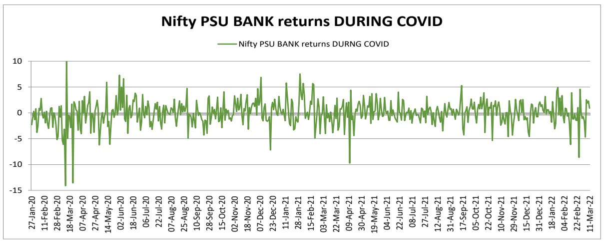

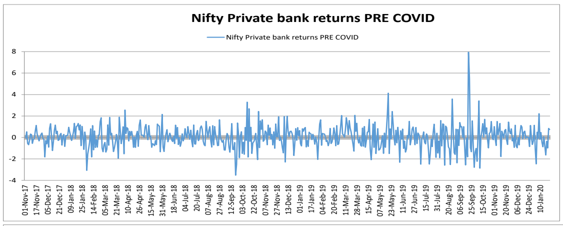

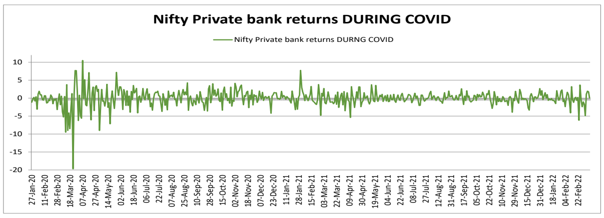

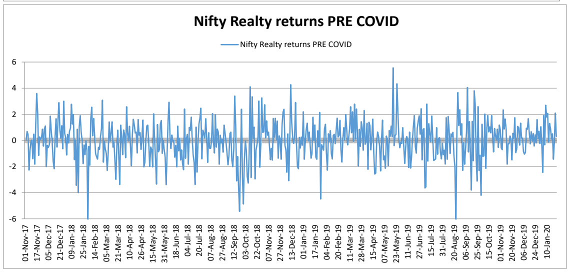

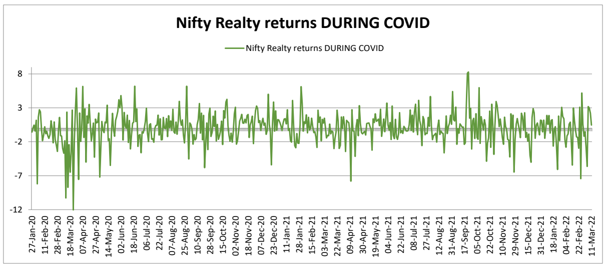

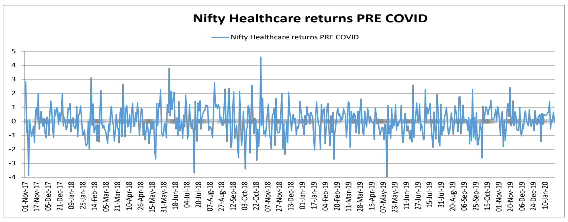

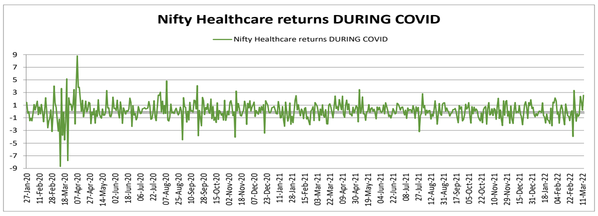

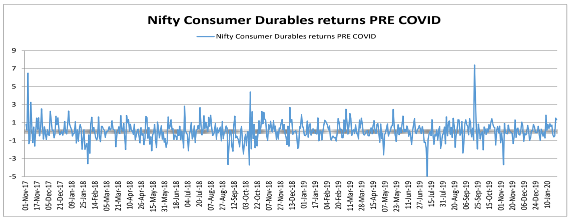

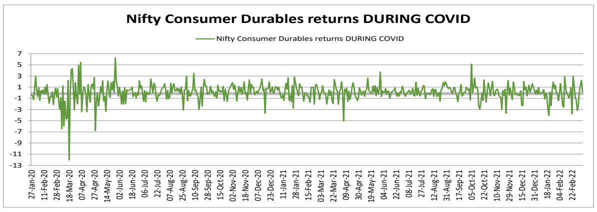

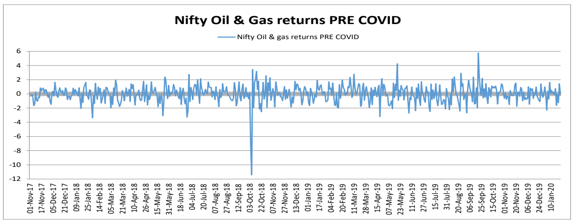

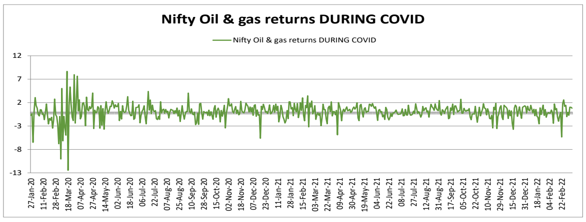

Graphs of closing prices of Nifty 50 and 14 sectoral indices with Rolling Hurst values for pre Covid (1/11/17 to 24 /1/20) and during Covid phase (27/1/20 to 11/3/22)

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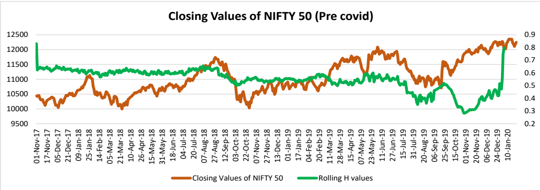

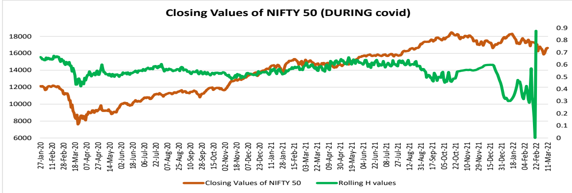

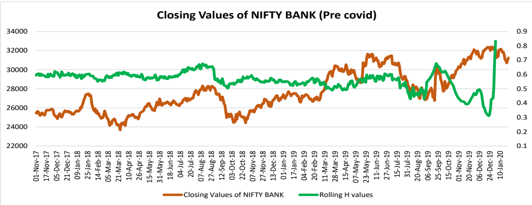

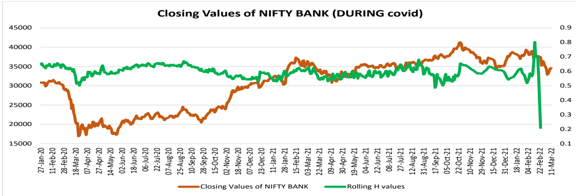

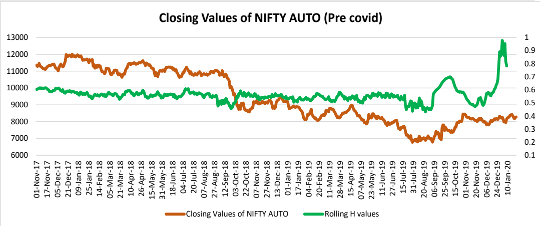

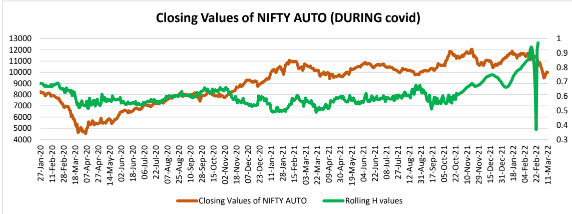

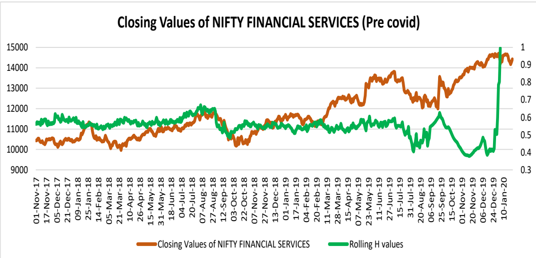

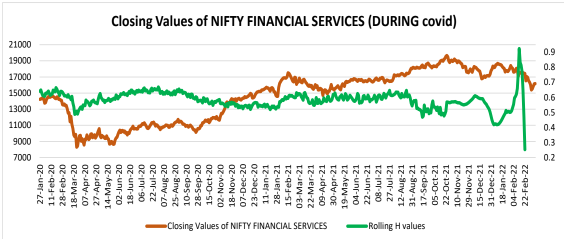

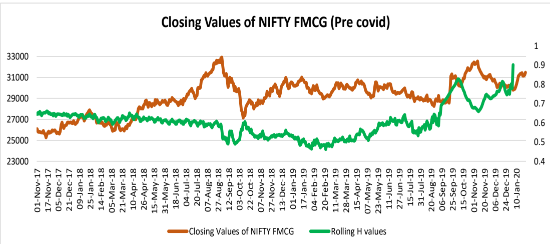

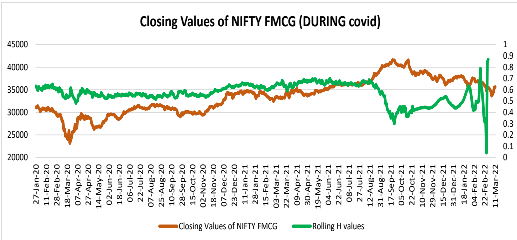

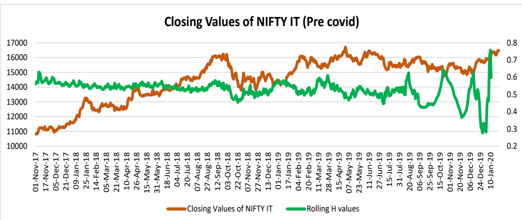

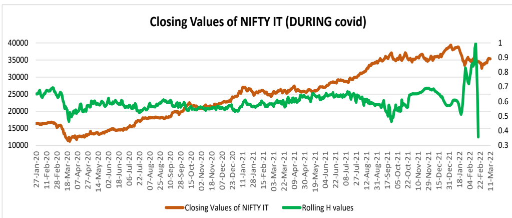

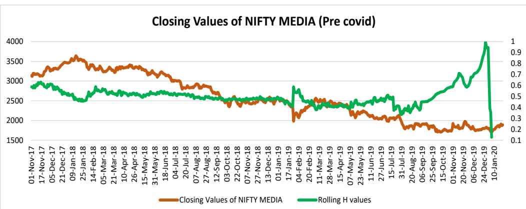

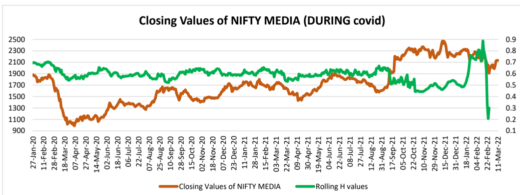

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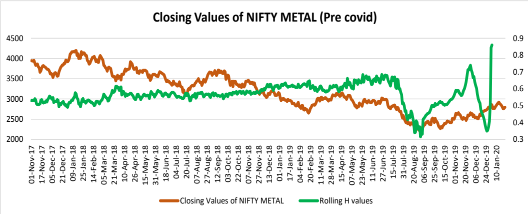

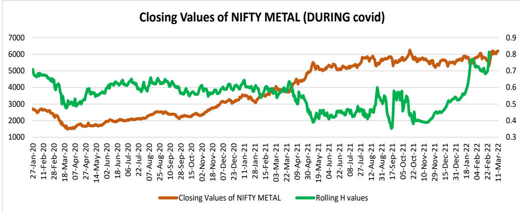

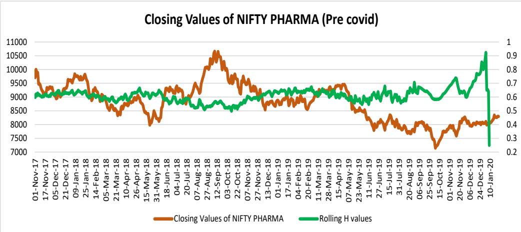

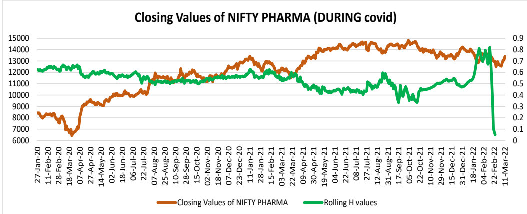

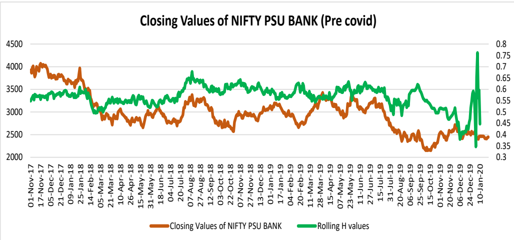

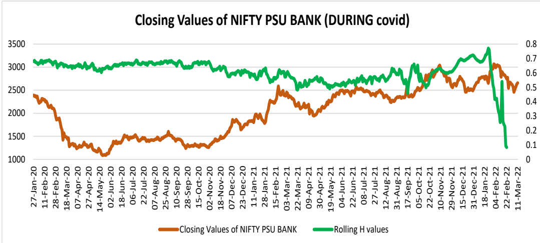

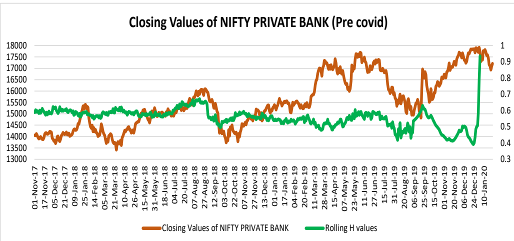

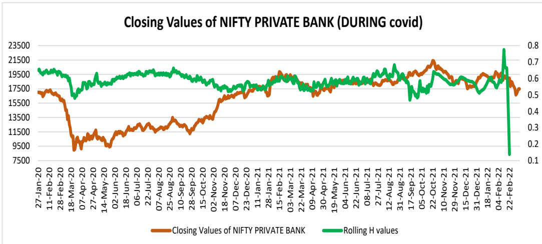

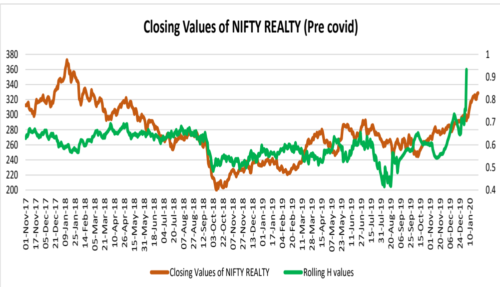

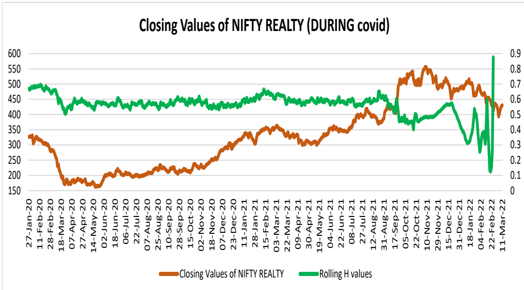

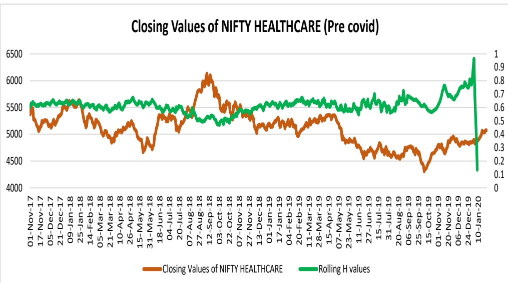

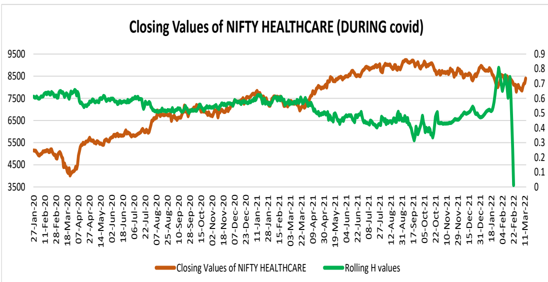

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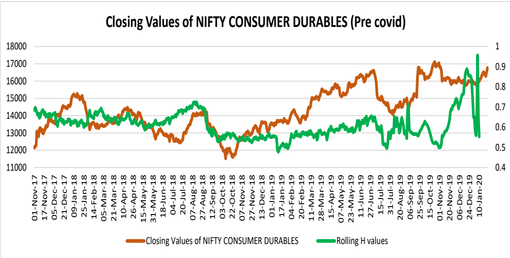

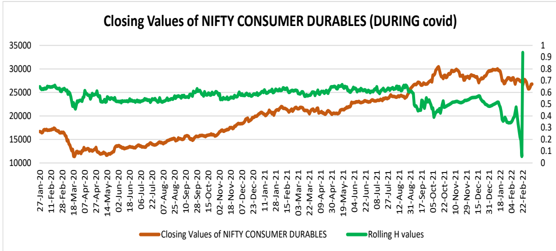

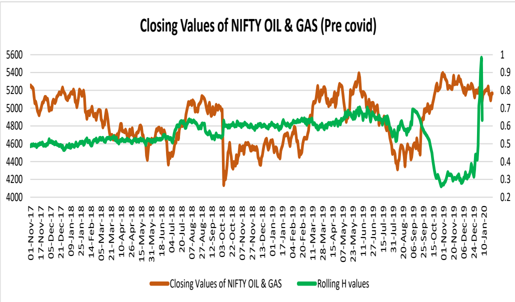

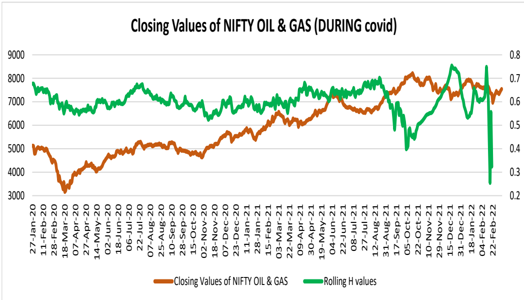

Findings for plots of Closing prices of indices and Rolling Hurst values

Though certain patterns of convergence and divergence maybe inferred from some of the charts plotted above, but a closer look reveals different fact. Any pattern found would be stock exchange as well as Sectoral index specific. The variety of behavior displayed by the closing values of these indices as well as Rolling Hurst Exponent series lack generalization.

Moreover, as can be seen from TABLE 4, Nifty 50 and all sectoral Indices on NSE have the rolling Hurst values >0.5 during both 'pre-covid' and 'during covid' periods. This lends further evidence in support of existence of long-term predictability effect in the Indian Stock market.

However, a conclusion can be drawn that long term predictability of Stock market is a time varying concept. As seen from charts of Closing Values- Rolling Hurst Values, the Rolling Hurst Exponent is time dependent variable and so, it can be inferred that even the market efficiency is also continuously time evolving for Indian Stock market. Thus, shows that market efficiency is not all or none condition but is a characteristic that varies continuously over time, with periods of inefficiency alternate with those of efficiency

DESCRIPTIVE STATISTICS ON CLOSE PRICES RETURNS RESULTS-

Table 1 and 2 :DESCRIPTIVE STATISTICS OF RETURNS OF15 INDICES-

		PRE COVID					
	Average:	Standard Deviation:	Skew:	Excess Kurtosis:	Median:	Minimum:	Maximum:
Nifty 50	2.90	0.82	0.43	3.46	0.05	-2.70	5.18
nifty bank	3.70	1.09	0.92	6.34	0.04	-2.87	7.98
nifty auto	-5.77	1.31	0.69	5.76	-0.08	-4.03	9.44
nifty financial services	5.88	1.06	0.65	4.90	0.09	-3.50	6.91
nifty FMCG	3.42	0.86	0.38	2.49	0.00	-2.99	4.31
nifty IT	7.65	1.07	-0.11	1.83	0.09	-4.79	4.69
nifty media	-9.20	1.74	-1.66	20.45	-0.03	-17.88	8.04
nifty metal	-6.26	1.58	0.00	0.15	-0.12	-5.15	5.52
nifty pharma	-2.87	1.23	0.04	1.10	-0.06	-4.47	5.08
nifty PSU bank	-8.58	1.99	0.17	0.92	-0.16	-6.08	7.69
nifty private bank	3.68	1.10	0.85	5.99	0.03	-3.52	7.94
nifty realty	0.92	1.57	-0.30	1.22	0.11	-6.37	5.56
nifty healthcare	-1.03	1.08	0.01	1.26	-0.02	-3.98	4.59
nifty con durables	5.85	1.11	0.62	6.51	0.04	-4.98	7.41
nifty oil & gas	-0.31	1.27	-1.44	13.49	0.01	-11.41	5.77

		DURING COVID					
	Average:	Standard Deviation:	Skew:	Excess Kurtosis:	Median:	Minimum:	Maximum:
Nifty 50	5.78	1.59	-1.75	16.18	0.17	-13.90	8.40
nifty bank	1.90	2.21	-1.33	11.58	0.10	-18.31	10.00
nifty auto	3.54	1.94	-0.97	9.91	0.13	-14.91	9.90
nifty financial services	2.16	2.10	-1.42	11.68	0.13	-17.36	8.91
nifty FMCG	2.34	1.33	-0.72	16.41	0.09	-11.20	7.99
nifty IT	14.43	1.74	-0.70	6.49	0.19	-10.06	8.64
nifty media	2.27	2.26	-0.06	6.16	0.07	-10.90	13.45
nifty metal	15.02	2.34	-0.80	3.20	0.36	-12.33	7.60
nifty pharma	9.07	1.59	-0.04	6.29	0.05	-9.35	9.86
nifty PSU bank	1.56	2.49	-0.65	4.36	0.05	-14.11	10.20
nifty private bank	0.31	2.27	-1.42	13.30	0.06	-19.70	10.49
nifty realty	5.09	2.37	-0.64	3.07	0.22	-12.05	8.30
nifty healthcare	9.50	1.46	-0.22	6.54	0.12	-8.69	8.80
nifty con durables	8.89	1.55	-1.30	9.43	0.19	-12.04	6.26
nifty oil & gas	7.18	1.75	-0.98	9.94	0.19	-12.44	8.68

Chart 1 and 2 : Risk and Average return comparison of all the 15 indices

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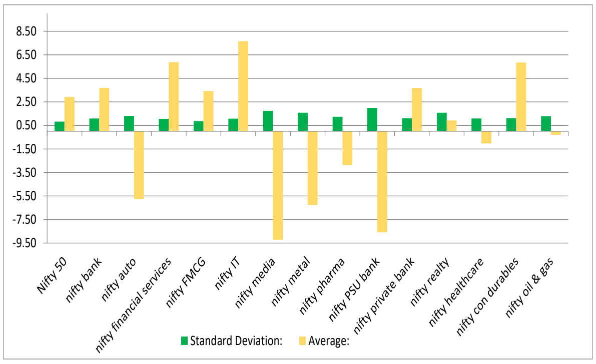

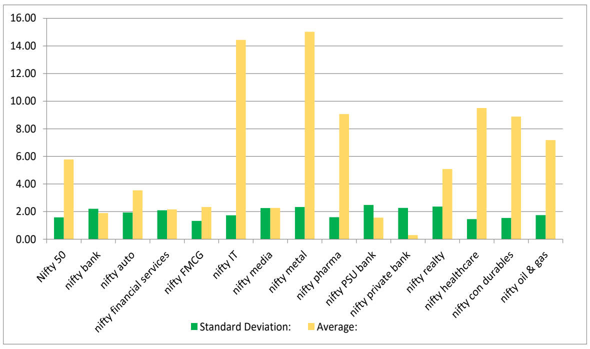

PRE COVID-

In the table 1 and Chart 1 above, the descriptive statistics methodology has been used for BROAD MARKET INDICE i.e. Nifty 50 and Nifty 14 SECTORAL INDICES. A total number of 550 observations have been used ranging from 1 Nov, 2017 to 24 Jan, 2020 as dates of pre-covid situation in India. Their closing values were used to calculate the daily percentage returns and then their descriptive statistics have been calculated in Microsoft Excel.

Here the mean values range from -0.09 to +0.07, while the standard deviation have larger values than mean showing that the data points are highly spread out over a wider range of values.

The skewness ranges between -1 to +1 showing the data are moderately skewed except Nifty media and Nifty oil & gas which are highly negative skewed stating that the data is more pushed towards the left-hand side and that if any negative shock takes place, the investors would expect to receive negative yield thus, leading to increase in disinvestment in the stock market.

Now the excess Kurtosis is >0, showing Compared to a normal distribution, its tails are longer and fatter, and often its central peak is higher and sharper, except for Nifty metal and PSU bank, which is almost 0, showing normal distribution.

DURING COVID-

In the table 2 and chart 2 above, the descriptive statistics methodology has been studied during- covid situation in India. A total of 529 observations have been used ranging from 27 Jan, 2020 to 11 March 2022. Their closing values were used to calculate the daily percentage returns and then their descriptive statistics have been calculated.

Here the mean shows all the positive values ranging from +0.03 to +0.15.

Standard deviation has been increased from pre- covid to during covid situation in India, this shows high level of risk in these Nifty indices in the stock market as compare to pre covid.

Here the skewness again ranges between -1 to +1 except Nifty 50, bank, Financial services, private bank and consumer durables which are highly negatively skewed as compared to the pre covid situation. This shows shock in these indices due to covid 19 pandemic.

Here the excess kurtosis of all the indices are >0, i.e. Positive values of kurtosis indicate that distribution is peaked and possesses thick tails. An extreme positive kurtosis indicates a distribution where more of the numbers are located in the tails of the distribution instead of around the mean.

Table 3 :STATIC HURST-

	STATIC HURST		
INDICES	PRE COVID	DURING COVID	RESULTS
Nifty 50	0.51	0.65	persistent
nifty bank	0.496	0.63	anti persistent to persistent
nifty auto	0.55	0.66	persistent
nifty financial services	0.49	0.63	anti persistent to persistent
nifty FMCG	0.55	0.63	persistent
nifty IT	0.55	0.63	persistent
nifty media	0.51	0.65	persistent
nifty metal	0.54	0.66	persistent
nifty pharma	0.57	0.62	persistent
nifty PSU bank	0.53	0.65	persistent
nifty private bank	0.49	0.63	anti persistent to persistent
nifty realty	0.63	0.67	persistent
nifty healthcare	0.59	0.61	persistent
nifty con durables	0.60	0.66	persistent
nifty oil & gas	0.51	0.63	persistent

Table 4 : ROLLING HURST

		MEAN Roll H
NIFTY 50	NIFTY 50 Roll H PRE COVID	0.546
	NIFTY 50 Roll H DURING COVID	0.546
NIFTY BANK	NIFTY BANK Roll H PRE COVID	0.558
	NIFTY BANK Roll H DURING COVID	0.595
NIFTY AUTO	NIFTY AUTO Roll H PRE COVID	0.560
	NIFTY AUTO Roll H DURING COVID	0.606
NIFTY FINANCIAL SERVICES	NIFTY FIN SER Roll H PRE COVID	0.548
	NIFTY FIN SER Roll H DURING COVID	0.582
NIFTY FMCG	NIFTY FMCG Roll H PRE COVID	0.604
	NIFTY FMCG Roll H DURING COVID	0.570
NIFTY IT	NIFTY IT Roll H PRE COVID	0.528
	NIFTY IT Roll H DURING COVID	0.599
NIFTY MEDIA	NIFTY MEDIA Roll H PRE COVID	0.505
	NIFTY MEDIA Roll H DURING COVID	0.590
NIFTY METAL	NIFTY METAL Roll H PRE COVID	0.567
	NIFTY METAL Roll H DURING COVID	0.553
NIFTY PHARMA	NIFTY PHARMA Roll H PRE COVID	0.612
	NIFTY PHARMA Roll H DURING COVID	0.533
NIFTY PSU BANK	NIFTY PSU BANK Roll H PRE COVID	0.567
	NIFTY PSU BANK Roll H DURING COVID	0.606
NIFTY PRIVATE BANK	NIFTY PRI BANK Roll H PRE COVID	0.555
	NIFTY PRI BANK Roll H DURING COVID	0.584
NIFTY REALTY	NIFTY REALTY Roll H PRE COVID	0.598
	NIFTY REALTY Roll H DURING COVID	0.559
NIFTY HEALTHCARE	NIFTY HEALTH Roll H PRE COVID	0.613
	NIFTY HEALTH Roll H DURING COVID	0.532
NIFTY CONSUMER DURABLES	NIFTY CON DUR Roll H PRE COVID	0.611
	NIFTY CON DUR Roll H DURING COVID	0.562
NIFTY OIL & GAS	NIFTY OIL & GAS Roll H PRE COVID	0.551
	NIFTY OIL & GAS Roll H DURING COVID	0.602

HURST EXPONENT-

The Hurst exponent is calculated to know the time dependency of the long-term behavior of the series. Since we are interpreting the impact of covid 19 pandemic on Indian stock market, we have taken 2 time series, one for 'Pre covid' starting from 1st Nov, 2017 to 24 Jan 2020 and 'During covid' series ranging from 27 Jan 2020 to 11 March 2022. The returns on closing price are calculated and based on that, Static Hurst and Rolling Hurst are calculated.

STATIC HURST- It is defined on the following intervals-

$0 \leq H < 0.5$- Data is fractal, anti-persistent series, negative correlation, it is also called as 'return to the mean', it shows that if there is growth/ high values in the previous period, then most likely in the next period a decline/ low values will begin and vice versa.

This series has high volatility as compared to random series. There is no long term memory in this series.

$H=0.5$, data is random. There is efficiency in market. There is no correlation. The present doesn't affect the future.

$0.5<H \leq 1$, data is fractal, persistent series, positive correlation. This is trend stable series. If the series increase (decrease) in the previous period, then it is likely to maintain this trend for some time in the future. There is long term memory in series.

The analysis of calculated static Hurst exponent before the Covid 19 (Pre covid) are presented in the table 3 above.

It is seen that hurst exponent for Nifty 50 is changed from 0.51→ 0.65 from pre covid to during covid time duration. This shows increase in hurst value which means higher level of herding and bubble in the market and therefore the risk component is high. This is due to economic shock faced by country due to nationwide lockdown and stock market came down.

In Nifty Auto, the values are 0.547→ 0.66 indicating long term memory both in pre and during covid, but as the values are getting higher, the more future values will be dependent on past values.

This behavior is seen on all Nifty sectoral indices except for Nifty Bank, Financial Services and Private Bank where the Hurst values changed from 0.49→ 0.63, i.e. from anti-persistent to persistent. Hence the 'pre covid' series has negative long term memory effect, that means increase (decrease) in the past values will have decrease (increase) effect in the upcoming future values that's why 'During covid' series have positive long term memory effect stating predictability of future values.

ROLLING HURST- A total of rolling window of 256 days are taken for the calculations areof Rolling Hurst . The reason for selection of 256 days is because a minimum of 256 days is required for the accurate calculation of Rolling hurst values and if values are calculated in a less than 256 days, then it can lead to generate inaccurate results and ultimately to wrong interpretation.

In the Table 4 above, we can see the mean of Rolling Hurst values in the both 'Pre-covid' and 'During covid' series is >0.5 showing persistence in all the indices. That means high predictability exists. Also, the specific values range from 0.5< H < 0.64, that means series is mild herding and creating mild bubble in the market.

6.0 CONCLUSION

The study shows that there is shift from anti persistent to persistent during the time of covid 19 pandemic (as per Static Hurst exponent values) i.e., there exists predictability in Nifty indices and their past values can be used for predicting the future values. Also, Rolling Hurst exponent mean values provides the result of predictability or long-term persistence which points to the emergence of market efficiency that can be exploited through the trend analysis . The mean of Rolling Hurst values in the both 'Pre-covid' and 'During covid' series is >0.5 for a major number of indices show persistence in all the indices and implies that the smart traders will be able to surpass the market return . It refutes the random walk hypothesis in the Indian stock market.

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