Measuring The Impact of Pandemic Disruption on Memory of Stock Markets. Do Stock Markets Remember?

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Abstract:

Memory in the stock prices is an important phenomenon of stock markets that poses a significant threat to the efficient market hypothesis of such markets and their equilibrium state. The presence of memory in both long-term as well as short-term security prices provides a potential opportunity for speculators and investors to forecast the prices and indulge in excess trading practices with the intention of making abnormal profits. The present study aimed at identifying and quantifying the long-memory and short-memory aspects of disruption caused by pandemic shock i.e. COVID 19 & focused on the time taken by the markets to overcome such shocks and to return to their equilibrium state. For this purpose, daily data of three important segments of NSE namely NIFTY FIFTY, NIFTY MIDCAP 50 & NIFTY SMALL CAP 50 were collected for a period of three years. Time series tools for example ACF, PACF & GPH (Geweke and Porter-Hudak) test were employed. The results so obtained indicated that there is significant short memory present in these indices that take considerably longer time to decay and long memory is also strongly indicated. The study, therefore, concludes COVID-19 disruptions still evidently subsisted in the security prices of these markets.

Keywords: Stock Markets, Long Memory, Short Memory, COVID-19 disruptions, Efficient Market Hypothesis

INTRODUCTION

Stock markets potentially evidence that what may initiate fast gaining in addition to forward growth as they pool investors' imminent income potentials. With this perspective, the new realities we're dealing with in the market could be observed. The financial system and the global economy have been seriously affected by the threats of disruption caused by COVID-19. The majority of the world's stock markets have suffered trillion-dollar losses, which has forced international financial institutions to lower their growth projections for 2020 and the

years following. The current study examines the impact of the COVID-19 pandemic on international stock markets. It has focused on the impact of recent and past pandemics on the financial markets. Despite all of the bad effects of the epidemic, there is still hope for a sharp rise and quick improvement in international financial markets. The COVID-19 outbreak caused a freefall in share prices before the stock market reached its peak on February 19, 2020. Since then, the world has evolved, impacting our lives, economies, and corporate fortunes a developing story that is represented in the upswing and downslide of share prices. Fundamental dynamics have gotten stronger, causing some organisations to advance at breakneck speed while others are being hit by hurricanes. The massive COVID-19 epidemic has had unexpected effects on the global environment and put the entire globe in peril. The COVID-19 outbreak was brought on by the SARSCoV2 virus, which first surfaced in Wuhan, Hubei Province, China, in December 2019 and quickly spread throughout the world. In addition to being a massive global health problem, this pandemic is also a major global economic crisis. As strict quarantine regulations are put in place to stop an unnamed sickness, the economic activity of several countries abruptly stops. Global economic activity has been hampered by the reduction in international travel. Most importantly, terror has disrupted normal consumer and corporate behaviour, which has led to anomalous market behaviour.

The epidemic generated uncertainty and danger, which is seriously affecting both developed and developing economies, including those in the United States, Spain, Italy, Brazil, and India. The financial market has reacted to this circumstance by changing dramatically and negatively. The economic instability associated with COVID-19 has had a considerable influence on the financial sector, which encompasses both the stock and bond markets.

The outbreak has caused the price of gold to soar considerably while the price of oil has drastically decreased. Firzli (2020) refers to this epidemic as "the larger financial crisis." In many countries, businesses have high levels of leverage, which further destabilises already unstable organisations. The pandemic has greatly raised the risk to the world's financial markets (Zhang et al., 2020). Investors have suffered enough losses as a result of fear and uncertainty.

For instance, the epidemic caused the global stock market to lose almost US$6 trillion in a single week from February 24 to February 28 (Ozili & Arun, 2020). The market value of the Standard & Poor (S&P) 500 indices has decreased by 30% after the COVID-19 outbreak. According to Azimili (2020), increased uncertainty affects the required rate of return and, as a result, the current market value of stocks.

LITERATURE REVIEW

Although there are limited existing empirical studies that have been undertaken on the effects of COVID-19 on the financial market have produced encouraging findings, according to the literature on the subject. Baret et al. (2020) found that the COVID-19 pandemic has led to a decline in the percentage of oil, shares, and bonds globally in their study on financial markets and banks. Social distance indicators had a detrimental impact on business efficiency, which led to reduced sales, higher operating costs, and cash flow issues. For the first time since 1987, the Financial Times Stock Exchange 100 index in Europe had a significant decline. 2020 (BBC News). According to Igwe (2020), the pandemic's shock will increase market volatility. The financial and economic systems of every nation may be severely impacted by this.

The asymmetric power GARCH model was used by Shehzad et al. (2020) to analyse the nonlinear behavior of the financial markets in the US, Italy, Japan, and China. According to the analysis, COVID-19 had a detrimental effect on the returns of the Stamp; P 500 stocks. On the Nasdaq composite index, it had no discernible impact. In the most seriously affected countries, Cepoi (2020) conducted an empirical analysis of the relationship between COVID-19-related news and stock market returns. This study used panel quantile regression and found that the stock market shows asymmetric dependent on COVID-19-related information.
It is not necessary to comprehend the epidemiological viewpoints in this case. Individuals who are currently well-informed should have a basic understanding of infectious diseases. The cure to fear is knowledge (Baldwin et al., 2020). In December 2019, the COVID-19 outbreak was officially reported in Wuhan, China, and it affected every continent except Antarctica (Hui et al., 2020). COVID-19 is a rare black swan occurrence, and we're completely uninformed of its existence, expansion, width, depth, scale, or even disappearance (He P. et al., 2020; He Q. et al., 2020). COVID-19 was declared a pandemic by the World Health Organization (WHO) on March 11, 2020. (Cucinotta and Vanelli, 2020).

Those who have been impacted by the pandemic have suffered. Almost everyone's lives and way of life have been impacted by it (Aqeel et al., 2021). Almost nobody has managed to avoid injury. While this epidemic is spreading fear and worry, a second pandemic of information and false information is keeping up with it (Koley and Dhole, 2020). The pandemic has quickly and significantly changed how people view the world. For the first time in human history, humans are faced with both the long-term effects of the disease and the irrefutable truth of their existence. The disease claimed the lives of more than 107 million people, caused 2.3 million

fatalities, and is still spreading today. The disease's rapid spread, which can result in 10,000 more cases from 100 contaminated cases in a short amount of time, is concerning.

There is a lot of literature on the influence of COVID-19 on many sectors like health, agriculture, industry, trade, and commerce, but just a few studies on its impact on the emerging economy's stock market have been done. The stock market has a significant impact on the economy. This study attempts to interpret the impact of COVID-19 on the Indian stock market, as India is one of the most important parts of the rising economy.

3 RESEARCH METHODOLOGY

The primary objective of this paper is to verify and measure the long memory of security prices and in particular to examine the impact of COVID-19 if any, India. For this purpose, three major broad based Indices Namely Nifty Fifty, Nifty Midcap Fifty and Nifty Small Cap Fifty were selected The daily closing prices were considered for all the variables for the period from 01-01-2019 to 10-05-2022 and were collected from NSE website.

Initially, the data that has been obtained for the study was subjected to their first differences to obtain the returns of the respective series by applying the following formula:

$$RETF_t = \frac{RETF_t - RETF_{t-1}}{RETF_t} * 100 \quad (1)$$

Where $REFT_t$ = the return on ETF's at day t

TESTS OF MEMORY

If the information is disseminated quickly, the opportunities for arbitrage disappear in a short period of time due to the price pressure formed by rational investors. To test both, short term and long memory we employ Autocorrelation Function Test and Partial Autocorrelation Test, Box-Pierce Q statistic and Geweke-Porter Hudak (GPH) Semi parametric test of long memory

3ai) Autocorrelation Function Test

To determine the level of autocorrelation in a time series, the autocorrelation function (ACF) test is looked at. The correlation between the most recent and most distant observations in the time series of ETF returns is measured and is defined as:

$$p_k = \frac{\sum_{t=1}^{n-k}(RETF_t - \overline{R}ETF)(RETF_{t+k} - \overline{R}ETF)}{\sum_{t=1}^{n}(RETF_t - \overline{R}ETF)^2} \quad \textbf{(2)}$$

where REFT is the return of the ETF and k is the number of lags. The standard error test and the Box-Pierce Q (BPQ) test are two crucial components for measuring autocorrelation. The significant autocorrelation coefficients at the group level are measured using the Box-Pierce Q test while the significant autocorrelation coefficients for individual lags are determined by the standard error test.

The standard error σ_k is defined as:

$$\sqrt{\frac{1+2\sum_{t=1}^{k-1}\theta_t^2}{N}} \quad \textbf{(3)}$$

where N is the total number of observations and k denotes the lag (k) autocorrelation. Box-Pierce Q is identified as:

$$N(N+2)\sum_{t=1}^{k}\frac{RETF_t^2}{N-t}. \quad \textbf{(4)}$$

Geweke-Porter Hudak (GPH) Semi parametric test of long memory:

Geweke-Porter Hudak [1](GPH) (1983) proposes a semi parametric approach to estimate'd'. The term semi parametric refers to the fact that the estimation problems involve a finite dimensional parameter of interest which is the long memory vector and an infinite dimension nuisance parameter (the spectral density). Therefore GPH proposed this method to extract 'd' which can capture the slope of the sample spectral density through an ordinary least square regression based on periodogram (Hiremath, G. S., & Kumari, J. (2015)[2]

Let the stationary process be defined as

$$f(\lambda) = f_0(\lambda) + \left[2\sin\left(\frac{\lambda}{2}\right)\right]^{-2d} \quad (5)$$

Taking logarithms on both sides of (12.1) and evaluating the spectral density at the Fourier frequencies,

$$\log f(\lambda_j)\log f_0(0) - d\log + \left[2\sin\frac{\lambda_j}{2}\right] + \log\left[\frac{f_0(\lambda_j)}{f_0(0)}\right] \quad (6)$$

The logarithm of the period gram $I(\lambda_j)$ may be written as

$$\log I(\lambda_j) = \log\left[\frac{I(\lambda_J)}{f(\lambda_j)}\right] + \log f(\lambda_j) \quad (7)$$

$$\log I(\lambda_j) = \log f_0(0) - d\log\left[2\sin\frac{\lambda_j}{2}\right] + \log\left\{\frac{I(\lambda_j)\left[2\sin\frac{\lambda_j}{2}\right]}{f_0(0)}\right\} \quad (8)$$

$$\text{By defining } y_j = \log I(\lambda_j) - d\,, \alpha = \log f_0(0), \beta = -d, xj = \log\left[2\sin\left(\frac{\lambda}{2}\right)\right]^2 \quad (9)$$

$$\epsilon_j = \log\left\{\frac{I(\lambda_j)\left[2\sin\left(\frac{\lambda}{2}\right)\right]^{2d}}{f_0(0)}\right\} \quad (10)$$

The long memory parameter "d" is estimated using the least square method as follows:

$$y_j = \propto + \beta x_j + \epsilon_j \quad (11)$$

$$f(\lambda_j) \sim f_0(0)\left[2\sin\left(\frac{\lambda}{2}\right)\right]^2$$

$$\epsilon_j \sim \log\left[\frac{I(\lambda_J)}{f(\lambda_j)}\right].$$

$$\hat{d}_m = -\frac{\sum_{j=1}^{m}(x_j - \bar{x})(y_j - \bar{y})}{\sum_{j=1}^{m}(x_j - \bar{x})(y_j - \bar{y})} \quad (12)$$

4 PRESENTATION AND ANALYSIS OF THE RESULTS

4.1 Table:1.1- UNIT ROOT TEST RESULTS

Indices	Augmented Dickey-Fuller Test of Stationarity			
	At Level		At First Differences	
	Test statistic	p-value	Test Statistic	p-value

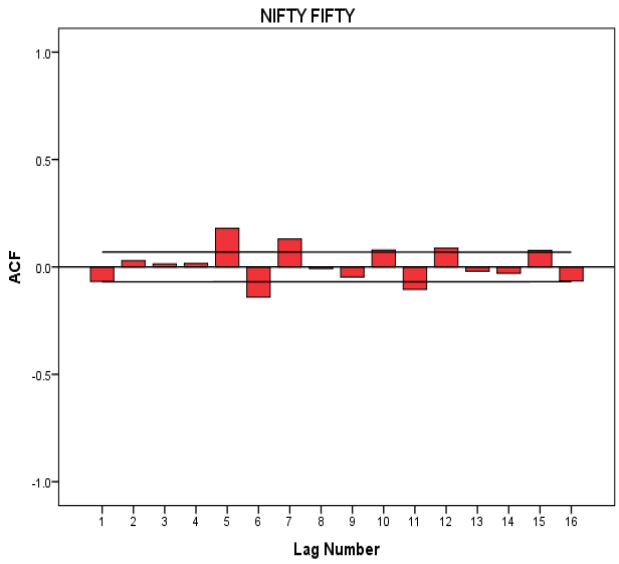
	(τ)		(τ)	
Nifty Fifty	**0.701**	**0.844**	**-29.00**	**0.000**
Nifty Midcap 50	**-0.371**	**.911**	**-27.22**	**0.000**
Nifty Small cap 50	**-0.657**	**.854**	**-23.65**	**0.000**

ADF Test of intercept without trend results report that all the variables are non-stationary at their levels. As shown in Table-1.1, the ADF Test Statistic **Tau** (τ) for Nifty 50, Nifty Midcap 50, and Nifty Small Cap50 are -0.701, -0.371, and -0.657 respectively all the p-values are greater than 0.05% level of significance and accordingly the null hypothesis of the presence of unit root cannot be rejected.

Further, when these variables were subjected to their first differences the **Tau** (τ) statistic reports values of -29.86, -28.96, and -32.55 for Nifty Small Cap 50, Nifty Small Cap 250, and Nifty Fifty respectively and all p-values are 0.00 which are lesser than 0.05% level of significance and highly significant. Hence all the variables are stationary at their first differences.

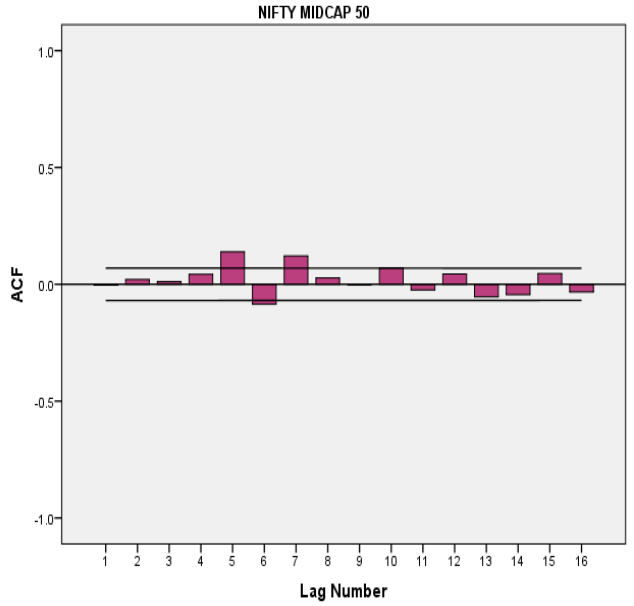
4.2 AUTOCORRELATION FUNCTION TEST RESULTS

4.2 (A) AUTOCORRELATION FUNCTION TEST RESULTS FOR NIFTY FIFTY SERIES



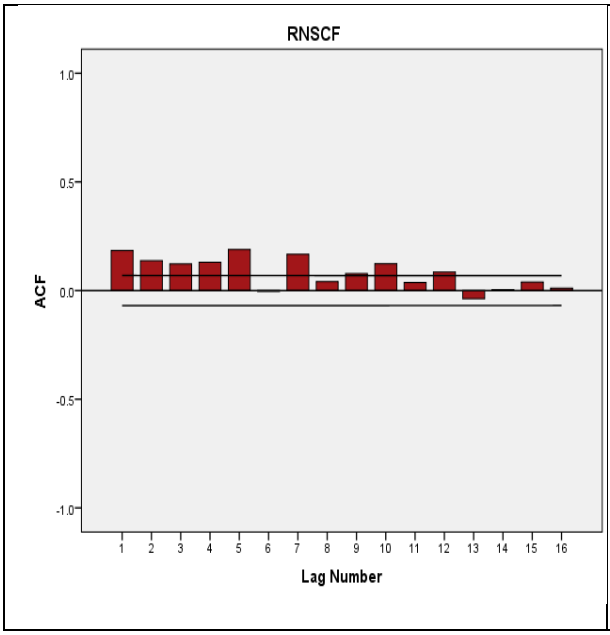
Lag	Autocorrelation	Std. Error[a]	Box-Ljung Statistic		
			Value	df	Sig.[b]
1	-.067	.035	3.782	1	.052
2	.030	.035	4.506	2	.105
3	.014	.035	4.672	3	.197
4	.016	.035	4.880	4	.300
5	.179	.035	31.724	5	.000
6	-.140	.035	48.173	6	.000
7	.130	.035	62.334	7	.000
8	-.008	.035	62.383	8	.000
9	-.047	.035	64.252	9	.000

4.2 (B) AUTOCORRELATION FUNCTION TEST RESULTS FOR NIFTY MIDCAP 50 SERIES



Lag	Autocorrelation	Std. Error[a]	Box-Ljung Statistic		
			Value	df	Sig.[b]
1	-.003	.035	.005	1	.942
2	.021	.035	.363	2	.834
3	.011	.035	.468	3	.926
4	.043	.035	2.010	4	.734
5	.139	.035	18.098	5	.003
6	-.085	.035	24.177	6	.000
7	.122	.035	36.588	7	.000
8	.028	.035	37.231	8	.000
9	-.001	.035	37.233	9	.000
10	.070	.035	41.333	10	.000

4.2 (B) AUTOCORRELATION FUNCTION TEST RESULTS FOR NIFTY SMALL CAP SERIES



Lag	Autocorrelation	Std. Error[a]	Box-Ljung Statistic		
			Value	df	Sig.[b]
1	.184	.035	28.232	1	.000
2	.137	.035	43.930	2	.000
3	.123	.035	56.468	3	.000
4	.130	.035	70.516	4	.000
5	.189	.035	100.205	5	.000
6	-.004	.035	100.217	6	.000
7	.167	.035	123.572	7	.000
8	.041	.035	124.989	8	.000
9	.078	.035	130.137	9	.000
10	.123	.035	142.888	10	.000

The Ljung-Box "Q" Statistic Test along with the test of autocorrelation was applied to the study's variables to determine whether autocorrelation exists in the Indices returns series. The test statistics suggest that the null of no autocorrelation of the series cannot be accepted in any of the Index Return series, which strongly suggests that autocorrelation existed at various lag lengths at the conventional 5% level of significance in all of the series. Even at the farthest 10^{th} lag, the autocorrelation does not diminish, confirming the persistence of autocorrelation in security prices. It is therefore concluded that there is short-term memory in the chosen Indices Series.

4.3 GEWEKE AND PORTER- HUDAK SEMI PARAMETRIC TEST

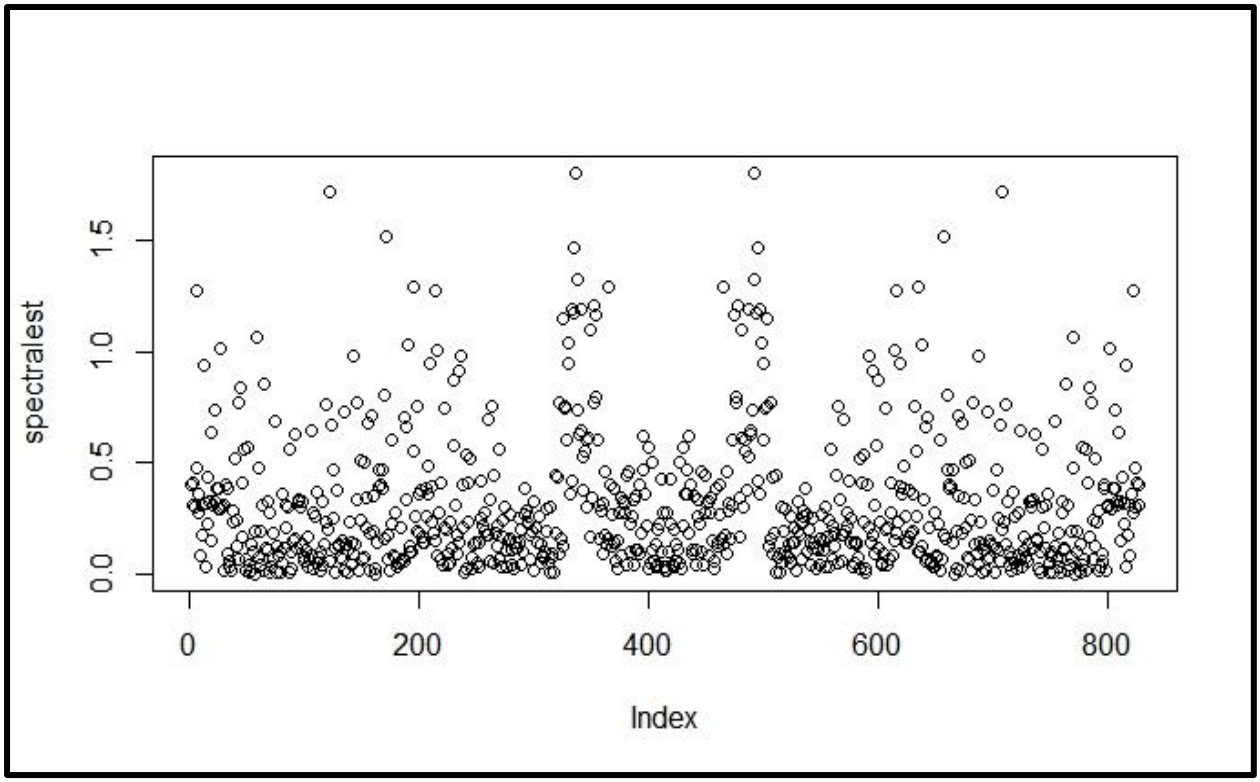
Long memory is a characteristic of prolonged autocorrelation in securities prices even at remote observations when the shocks would never dissipate for a long period of time. This phenomenon encourages investors to use prediction-based trading tactics in order to generate abnormal profits.

Furthermore, the prevalence of long memory is a significant danger to efficient market theory and financial market economic health. The current study, therefore, aimed to determine the presence of long memory of the impact of COVID-19 in Indian stock markets using the Geweke and Porter- Hudak Semi-Parametric Test.

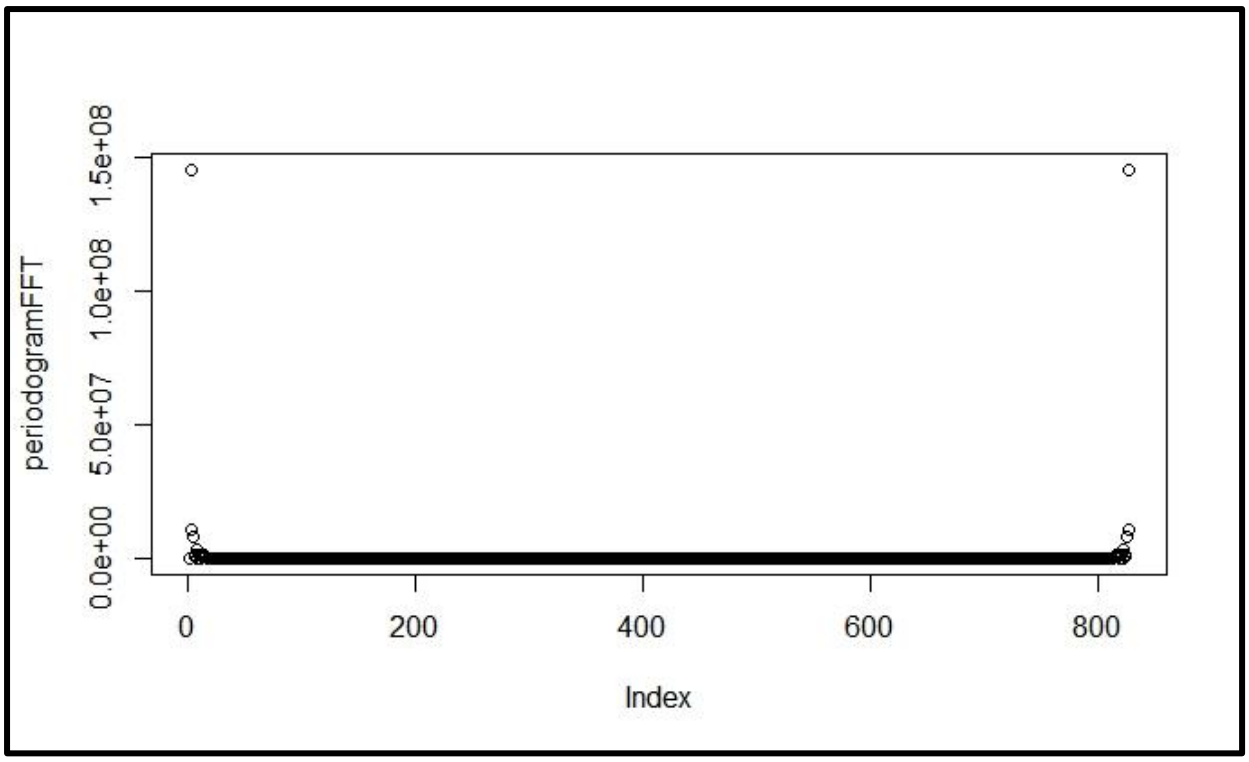
4.3 (A) GEWEKE AND PORTER- HUDAK SEMI-PARAMETRIC TEST RESULTS OF THE INDICES SERIES

INDEX RETURNS	**Geweke and Porter- Hudak Semi Parametric Estimator of "d"**		
	***m* = 0.50**	**standard deviation**	**standard error**
NIFTY 50	**0.005**	**0.14**	**0.08**
NIFTY MID-CAP 50	**1.09**	**0.14**	**0.12**
NIFTY SMALL CAP 50	**0.170**	**0.14**	**0.12**

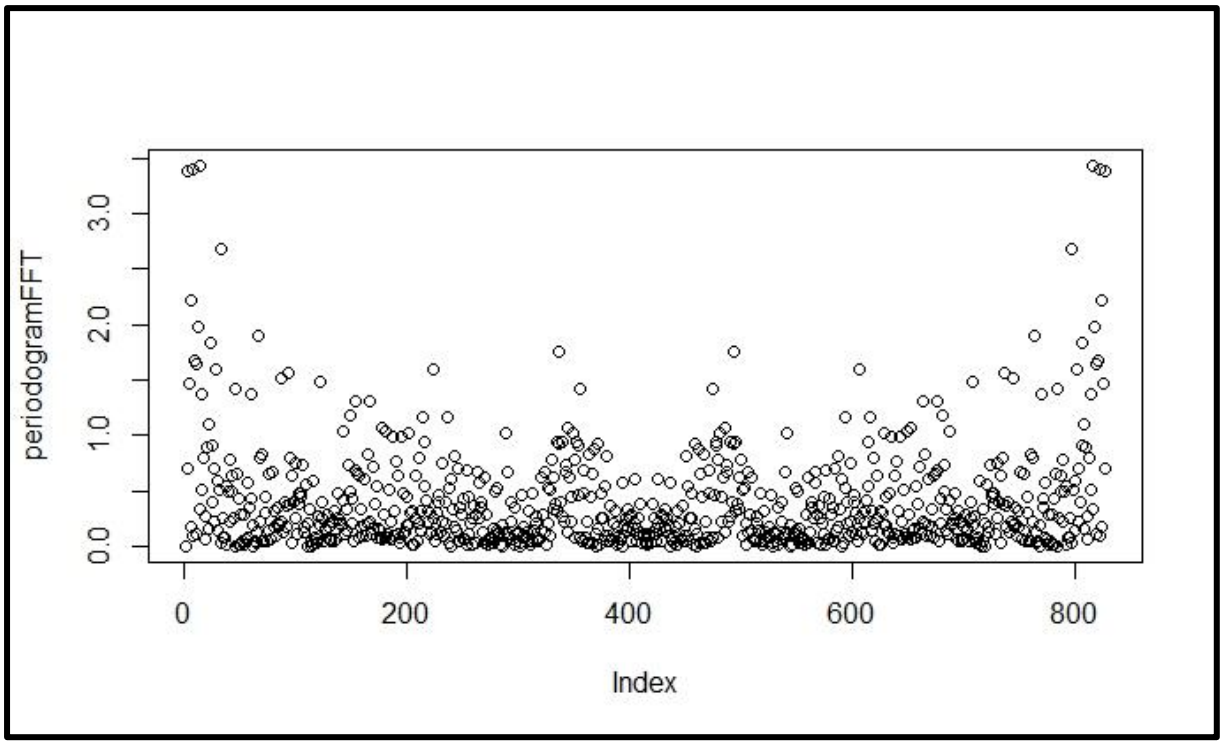
4.3 (B) Graphical Representation of Fractionally Differenced NIFTY 50 Series.



4.3 (C) Graphical Representation of Fractionally Differenced NIFTY MIDCAP 50 Series



4.3 (C) GRAPHICAL REPRESENTATION OF FRACTIONALLY DIFFERENCED NIFTY SMALL CAP 50 SERIES



Geweke and Porter- Hudak Semi Parametric Test Results of Indices returns are presented in tables above. The fractional difference estimate ‘d’, is estimated for one special ordinate of the

periodogram of returns to capture the possibility of Long Memory, and the ordinates are set at $T^{0.50}$

The GPH 'd' estimate is given in the first column and the respective standard deviation is given in the second column onwards. the 'd' estimates of the Nifty Fifty Index reveal a positive 'd' estimate of 0.00054 along with a standard deviation of 0.14 and a standard error of 0.08. Therefore, it can be inferred that the Long Memory is significantly present at 0.5 ordinate of Nifty Fifty.

Nifty Midcap 'd' is estimated at 1.09 along with a standard deviation of 0.14 and a standard error of 0.12. This leads the study to conclude that the long memory is significantly present in Nifty Midcap Index which is evidenced by the respective fractional differenced plot.

Nifty Small Cap Index registers a positive 'd' 0.170 along with a standard deviation of 0.14 and a standard error of 0.12. This leads the study to conclude that the long memory is significantly present in Nifty Small Cap Index which is evidenced by the respective fractional differenced plot.

SUMMARY OF FINDINGS

The current study concludes that Long Memory of the impact of COVID-19 is considerably prevalent in the Indian Stock and Forex markets based on two commonly utilised tests that were used to verify Long Memory. It should also be emphasized that persistence is evident in all of the variables considered.

Outliers in the form of news impact are detected in several of the variables, combined with widely spread values distant from the equilibrium values, implying that the information decaying process is particularly sluggish in these markets.

When the performance of stock markets and forex markets is examined, it is evident that it is feasible to discern patterns of decline and rise that are also extended in character, and prediction is nearly conceivable in these markets.

When the behavior of the stock markets is examined, it is evident that it is feasible to discern patterns of decline and rise that are also extended in character, and prediction is nearly conceivable in these markets. Several crashes and severe corrections have occurred in India as a result of such excess strategy-based trading, which is the immediate answer to trend and patterned-based trading.

As a result, the current study suggests that an appropriate regulatory framework is required, and microstructural adjustments are inevitable for the effective transmission of news arrivals and shock decay.

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