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The Performance of Top Coronavirus Vaccine Stocks during COVID-19 Pandemic: A Multifractal Analysis

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COVID-19 Pandemisinde En Üst Koronavirüs Aşı Hisselerinin Performansı: Çoklu Fraktal Analiz

Abstract

This study assesses how the coronavirus pandemic (COVID-19) affects the 5-day week multifractal properties of five vaccine stocks (i.e., Pfizer, BioNTech, Moderna, Johnson&Johnson, and AstraZeneca) using weekday index data ranging from 9 December 2019 to 6 January 2022. The main concern is to document whether the presence of herd investing and the level of market efficiency changed between pre-vaccination (i.e., 9 December 2019 - 8 December 2020) and post-vaccination (i.e., 9 December 2020 - 6 January 2022). The generalised Hurst exponents are calculated through multifractal detrended fluctuation analysis. Overall, the empirical results show multifractality for each vaccine stock during the COVID-19 outbreak. Besides, the efficiency level differs among the vaccine stocks based on multifractal properties. The results indicate that the post-vaccination period is more prone to herd investing in BioNTech and Moderna stocks. Considering the impacts of this far-reaching outbreak, the highest MLM (inefficiency) index value is also attributed to BioNTech before and after the COVID-19 vaccination process.

Keywords : Vaccine Stocks, Efficiency Index, Generalised Hurst Exponent, Herding Behaviour, COVID-19.

JEL Classification Codes : C1, G1, G14, G15.

Öz

Bu çalışma, 9 Aralık 2019-6 Ocak 2022 arasında beş aşı hissesinin (Pfizer, BioNTech, Moderna, Johnson&Johnson ve AstraZeneca) koronavirüs pandemisinde işgünü haftalık verileri temelinde çoklu fraktal özelliklerinin nasıl etkilendiğini araştırmaktadır. Çalışmanın temel amacı sürü yatırımının ve piyasa etkinlik düzeyinin aşılama dönemi öncesinde (9 Aralık 2019 - 8 Aralık 2020) ve sonrasında (9 Aralık 2020 - 6 Ocak 2022) değişiminin varlığını ortaya koymaktır. Genelleştirilmiş Hurst üsleri çoklu fraktal eğiliminden arındırılmış dalgalanma analizi yoluyla hesaplanmaktadır. Genel olarak, ampirik sonuçlar COVID-19 salgını sırasında her aşı hissesi için çoklu fraktal varlığın mevcut olduğunu göstermektedir. Ayrıca çoklu fraktal özelliklere göre etkinlik düzeyi aşı hisseleri arasında farklılık göstermektedir. Elde edilen sonuçlar aşılama sonrası dönemin BioNTech ve Moderna hisse senetleri için sürü yatırımına daha yatkın olduğunu göstermektedir. Güncel salgının etkileri göz önüne alındığında COVID-19 aşılama sürecinin öncesi ve sonrasında en yüksek MLM (etkinsizlik) indeks değerinin BioNTech'e ait olduğu ortaya konmaktadır.

Anahtar Sözcükler : Aşı Hisseleri, Etkinsizlik Endeksi, Genelleştirilmiş Hurst Üssü, Sürü Davranışı, COVID-19.

1. Introduction

The official authorities assume the vaccines as one of the chief lines of defence against the coronavirus pandemic. While the COVID-19 pandemic hard hit the stock markets, many investors' interests have shifted towards vaccine stocks in which their returns peculiarly gained momentum in the stock market; the academic studies have been felt short to assess the growth performance of vaccine stocks. Given the recent rise in COVID-19 concerns amongst individual and institutional investors, vaccine stocks could be worth mentioning to realise how their financial values have skyrocketed in nothing flat over against the other stocks.

A glance at the existing literature indicates that pre-COVID-19 behaviours still prevail for investigating specific stocks during the crisis. While more recent studies have expanded their analyses on different markets (e.g., cryptocurrencies) with newly implemented methods, adapting those procedures to investigating vaccine stocks over the coronavirus pandemic has lagged behind the growing interest in evaluating the stock market crash during the COVID-19. However, to the author's knowledge, the investigation of vaccine stocks in terms of their performance over the coronavirus pandemic has not been fulfilled using the multifractal analysis. For this reason, the performance of top coronavirus vaccine stocks is the primary concern of this study which consists of the after-disease period of the COVID-19 process. The main contribution of this study is an attempt to determine the COVID-19 impact on the performance of top coronavirus vaccine stocks.

This paper is structured as follows: A summary of the recent literature is introduced in the second section. The data set is described in the third section, and the methodological approach is explained in the fourth section. The empirical findings are represented in the fifth section. The last section concludes.

2. State of the Art

A stable stock market ought for the entire financial sector, covering both markets and institutions, and the economic system stresses the importance of security and safety for financial investment. The volatility spillover and explosive bubble resulting from a speculative-led motive can be the source of a market crash for a certain period. Therefore, the analytical structure of stability conditions might be highly appreciated for innovative techniques for the financial sector. The Gaussian-based distribution models of former techniques document that they could be stronger in explaining the future of capital markets. However, the recent methods (e.g., multifractal models) cover different algorithmic toolboxes to forecast several financial risks and potential downturns in more accurate patterns. In that vein, the possibility of crashes and crises in the financial sector can be introduced using the logical structure developed by Mandelbrot (1975) within the context of fractal theory. Following that pattern of analysis procedure, the empirical form is based on a recently initiated method, the efficient multifractal detrended fluctuation analysis (MFDFA), to characterise the variability and uncertainty in time series. In particular, extracting the fluctuations on different temporal scales leads to assessing the strength and correlations in the underlying stochastic properties, their scaling behaviour, as well as the level of fractality (Gorjão et al., 2022).

Techniques such as MFDFA evolved to analyse the multi-connected structures of financial time series (Rizvi et al., 2014; Aslam et al., 2022) with the presence of multifractality in financial time series indicating possible market inefficiency (Zunina et al., 2008; Lee et al., 2017; Tiwari et al., 2019). While the use of the MFDFA approach is rarely used in existing literature, some of the studies are worth to be mentioned for analysing stock market fluctuations. For instance, Mensi et al. (2017) utilise the MFDFA approach to investigate the efficiency level of the sectoral stock markets. The empirical findings imply a harsh difference in time effects on the performance of sectoral stock markets. The short-run period shows a more moderate efficiency relative to the long-run period. In addition, the results show that the post-financial crisis has witnessed a higher inefficiency rate for those markets. Besides, Aslam et al. (2020a) investigate the efficiency of frontier stock markets using the MFDFA approach and find that the degree of multifractality varies among frontier stock markets, implying that they exhibit long-range dependence.

Lee et al. (2017) find that the multifractal nature of the U.S. stock indices is asymmetric when the index-based model is used to detect asymmetric multifractality than the return-based model. The MFDFA approach was also investigated to detect the asymmetry of the stock markets. Other empirical studies developed the existing relations between multifractality and stock market efficiency. Amongst these, the study formed by Arshad et al. (2019) finds that emerging Asian stock markets have long-term stability and efficiency even though the financial crises have a short-term negative impact on the efficiency of emerging markets. Maganini et al. (2018) also find that the Brazilian indices are multifractal but vary regarding the selected assets.

The impact of the latest pandemic disease (i.e., COVID-19) on financial markets was also investigated by a limited number of studies in the literature, considering the MFDFA approach. For instance, Aslam et al. (2020b) employ this approach to analyse the effect of COVID-19 on the intraday multifractal properties of European stock markets using high-frequency data. The empirical findings show that the Austrian stock market has the least efficient, while Spain has the most efficient stock market among the markets considered during the COVID-19 pandemic. However, the rest of the other markets, such as Belgium, Italy, and Germany, remain in the middle. Mnif et al. (2020) also study the level of cryptocurrency efficiency through multifractal analysis before and after the coronavirus pandemic and found that there is a positive impact of COVID-19 on cryptocurrency market efficiency.

3. Data

The sample includes five vaccine stocks extracted from Yahoo Finance on a 5-day week basis frequency from 9 December 2019 (the World Health Organization (WHO) recommended 2019-nCoV and 2019-nCOV acute respiratory disease) to 6 January 2022. The sample is divided into two periods before the COVID-19 vaccination (9 December 2019-8 December 2020) and after the COVID-19 vaccination (9 December 2020-6 January 2022). In this context, the data was constructed to analyse the post-performance of vaccine stocks during the COVID-19 outbreak regarding their vaccination-based classification.

The 5-day week returns of vaccine stocks are represented as:

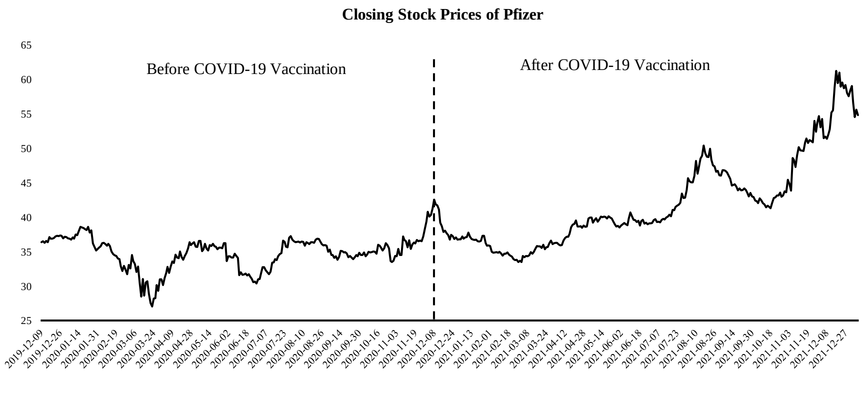
$$r_t = log\left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) = \%\Delta P_t \tag{1}$$

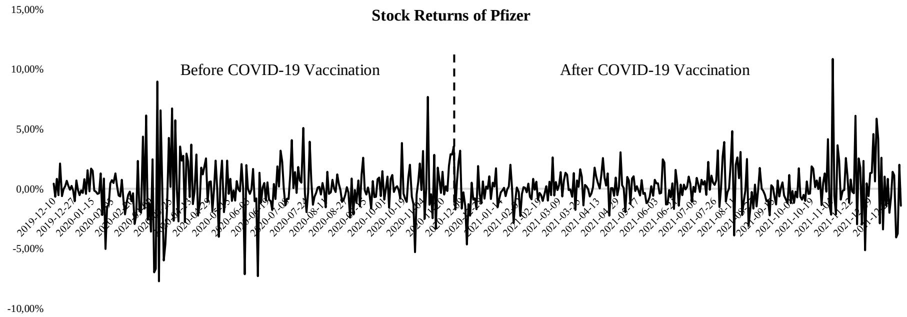
where r_t is the vaccine stock return at time *t*, and P_t and P_{t-1} are the vaccine stock values at time *t* and *t-1*, respectively. Regarding the net return over 5-day week data *t*, Fig. 1 depicts the evolution of 5-day week vaccine stocks' prices and returns. Table 1 also describes the data.

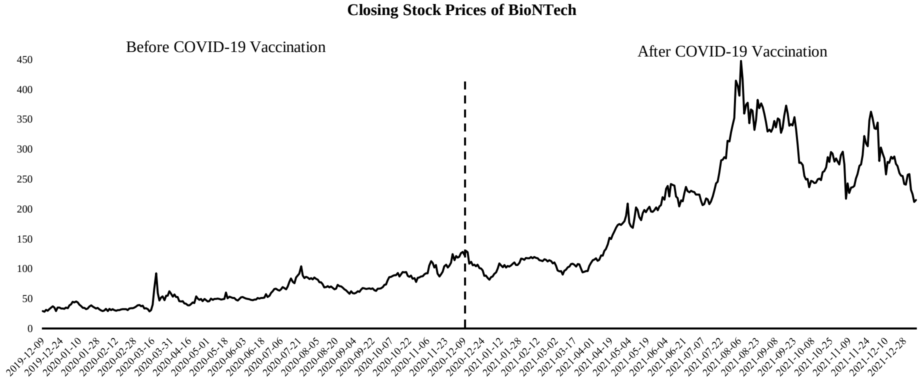
Table: 1
Data Description

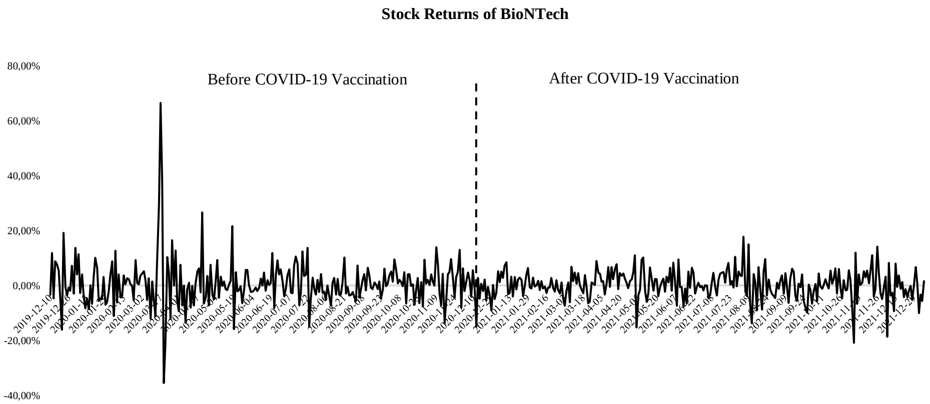
Vaccine Stocks	Period	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B
Pfizer	Before	34.8	35.2	41.3	27.1	2.35	-0.67	3.85	27.0
	After	42.1	39.9	61.3	33.5	6.48	1.04	3.41	50.6
	Total	38.6	36.7	61.3	27.1	6.14	1.45	5.12	283.5
BioNTech	Before	60.5	54.7	128.1	28.0	23.7	0.65	2.68	19.4
	After	216.1	220.5	447.2	81.5	91.1	0.20	1.95	14.3
	Total	141.1	102.6	447.2	28.0	103.1	0.87	2.52	70.9
Moderna	Before	55.2	61.5	169.9	17.7	28.9	0.89	4.89	71.9
	After	240.9	219.7	484.5	104.5	99.6	0.57	2.09	24.3
	Total	151.3	125.1	484.5	17.7	118.9	0.89	2.76	71.6
Johnson&Johnson	Before	145.2	147.0	155.5	111.1	6.45	-2.03	8.73	520.3
	After	164.8	164.3	179.5	149.1	5.73	-0.02	3.03	0.002
	Total	155.4	153.9	179.5	111.1	11.5	-0.30	2.85	8.45
AstraZeneca	Before	51.7	52.9	61.1	37.7	4.17	-1.02	3.95	53.6
	After	55.3	56.3	63.8	41.2	4.19	-0.15	1.87	15.2
	Total	53.6	53.9	63.8	37.7	4.54	-0.44	3.38	20.2

Figure: 1
The Prices and Returns of 5-Day Week Vaccine Stocks

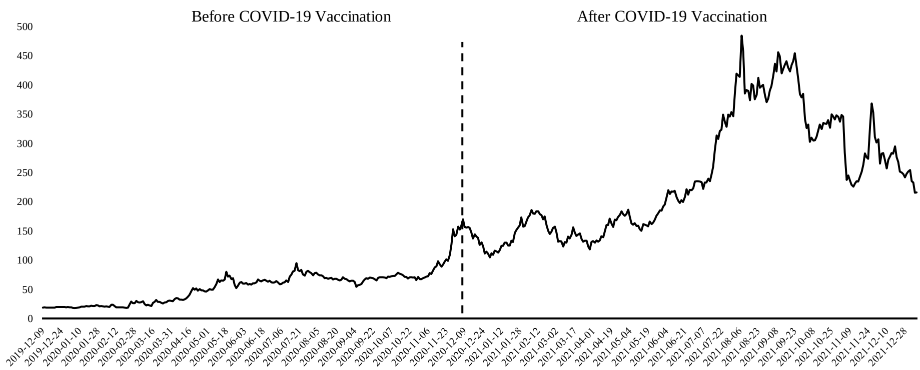



Stock Returns of Pfizer
Before COVID-19 Vaccination
After COVID-19 Vaccination
15,00%
10,00%
5,00%
0,00%
-5,00%
-10,00%

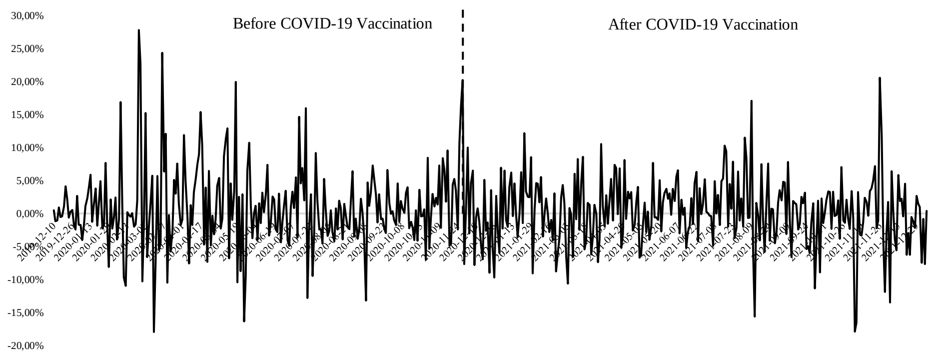

Closing Stock Prices of BioNTech
Before COVID-19 Vaccination
After COVID-19 Vaccination
450
400
350
300
250
200
150
100
50
0


Stock Returns of BioNTech
Before COVID-19 Vaccination
After COVID-19 Vaccination
80,00%
60,00%
40,00%
20,00%
0,00%
-20,00%
-40,00%

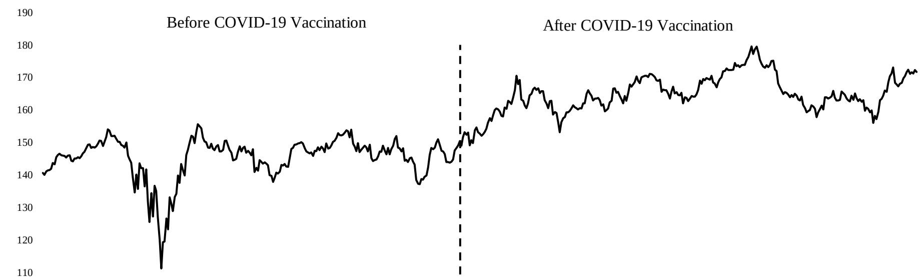
Closing Stock Prices of Moderna



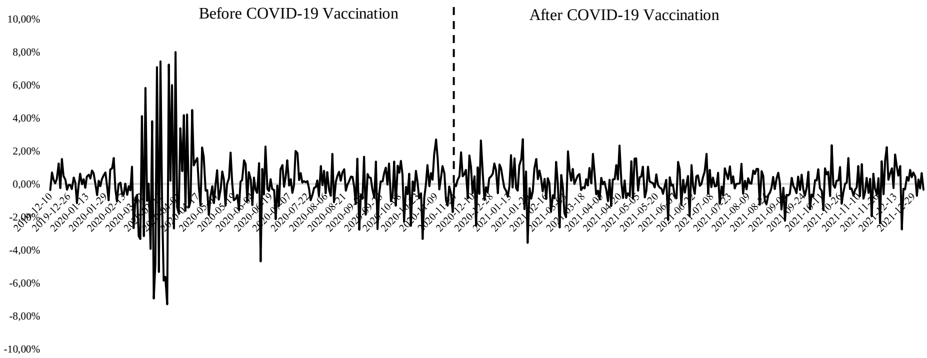
Stock Returns of Moderna



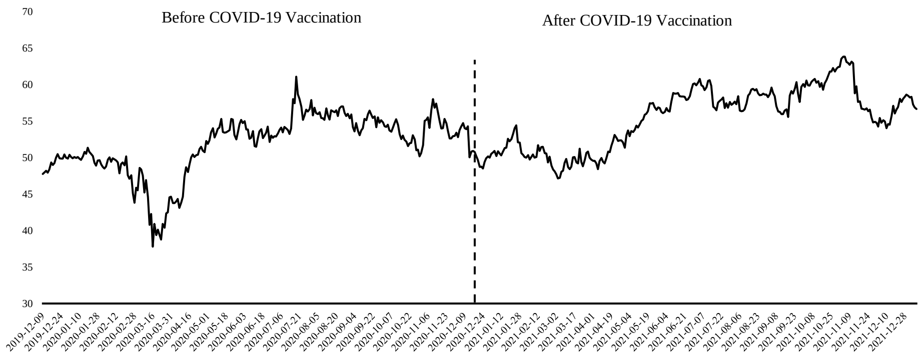
Closing Stock Prices of Johnson&Johnson



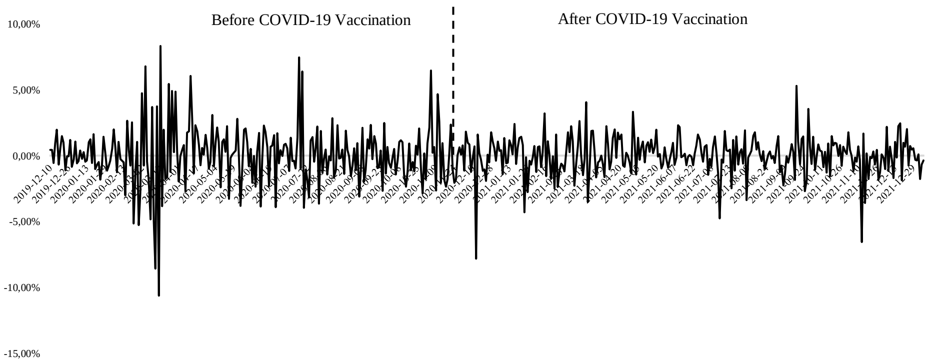
Stock Returns of Johnson&Johnson



Closing Stock Prices of AstraZeneca



Stock Returns of AstraZeneca



4. Methodology

This empirical section explains the fractal theory used to assess top vaccine stocks' performance and investigates their degree of efficiency during the COVID-19 pandemic.

4.1. The MFDFA Approach

According to Kantelhardt et al. (2002), the MFDFA approach can be explained through 5 steps. In Step 1, the profile or cumulative sum *Y(i)* is examined as it is depicted in Eq. (2):

$$Y(i) = \sum_{k=1}^{i} |x(k) - \bar{x}| \quad (2)$$

where $\bar{x}$ shows the mean value of each series. The major aim of committing that process is to convert a white noise process into a random walk.

In Step 2, the Y_t is divided into N_s, which equals N/s segments of equal length s.

Besides Step 2, the next step (i.e., Step 3) consists of the estimation for local trend through the least-square fitting polynomial $\tilde{Y}_\upsilon$ for each segment of equal length υ.

The crucial implication is a detrending process, which goes through for a range of different window sizes s represented in Eq. (3) as follows:

$$F_x^2(\upsilon) = \frac{1}{s}\sum_{k=1}^{x}(Y_\upsilon(k) - \tilde{Y}_\upsilon(k))^2 \quad (3)$$

To complement Step 3, the next step (i.e., Step 4) measures the q^{th} order fluctuation function F_q where the segments are close to the mean:

$$F_q(S) = \left\{\frac{1}{2N_s}\sum_{\upsilon=1}^{2N_s}[F_s^2(\upsilon)]^{\frac{q}{2}}\right\}^{\frac{1}{q}} \quad (4)$$

where q is different from zero.

The last step (i.e., Step 5) ascertains the scaling behaviour of the fluctuation functions where each value of q versus s is plotted by *log-log* of $F_q(S)$ as represented in Eq. (5):

$$F_q(S)\ \alpha\ S^{H(q)} \quad (5)$$

To get rid of the overfitting problem, the order at $m=1$ is selected in the empirical analysis, as explained in the work of Lashermes et al. (2004) and Mnif et al. (2020).

4.2. Generalised Hurst Exponent (GHE)

One of the major areas of utilisation for Hurst exponent is detecting bubble explosions in financial markets (Hurst, 1951). In simplicity, this consists of two alternative situations where H is higher than 0.5 or vice versa. It is widely accepted that the series are anti-persistent (persistent) with no shape (with a clear shape) and minimum (maximum) fractal quotient when $H > 0.5$ ($H < 0.5$). In addition, the H can be equal to 0.5 ($H = 0.5$), which means that the series follows a random walk process and are entirely stochastic. The theoretical sense for those alternatives leads to arguing that there is a bubble-type behaviour when $H > 0.5$ but none in the case of $H < 0.5$. On the other hand, when $H = 0.5$, the bubble formation is neutral for the market as a whole.

The primary issue is to check whether the series are rough by estimating the Hölder (Hurst) exponent (H) (Mandelbrot & van Ness, 1968) in which the fractal dimension is defined as follows:

$$d = 2 - H \text{ when } 0 < H < 1 \tag{6}$$

and

$$d = 1.5 - \alpha \text{ when } -0.5\alpha < 0.5 \tag{7}$$

The estimated $h(q)$ from MFDFA can also be represented as a function of the Renyi exponent $\tau(q)$:

$$\tau(q) = qh(q) - 1 \tag{8}$$

The multifractal process $\tau(q)$ for the scaling function is concave but linear for the monofractal process. The $\tau(q)$ is alternatively measured from the generalised Hurst exponent (GHE) as represented in Eq. (9):

$$H(q) = \frac{1+\tau(q)}{q} \tag{9}$$

or from the generalised fractal dimension as represented in Eq. (10):

$$D(q) = \frac{\tau(q)}{q-1} \tag{10}$$

Following the study of Di Matteo (2007), the GHE procedure can be depicted based on fractal geometry. In that context, the q-order moment $K_q(\mu)$ of the $X(t)$ distribution of increments is shown as follows:

$$K_q(\mu) = \frac{|X(t+\mu) - X(t)|^q}{|X(t)|^q} \tag{11}$$

where μ is the time interval between increments and q is a higher order than zero.

By using the scaling law, one can represent the GHE as shown in Eq. (12):

$$K_q(\mu) \approx \alpha\, \mu^{qH(q)} \tag{12}$$

The implementation of Legendre transformation allows for obtaining the following relations in Eq. (13):

$$\alpha = H(q) + q.H'(q) \tag{13}$$

So that, the singularity spectrum *f(α)* is described as follows:

$$f(\alpha) = q\,\alpha + q.H(q) + 1 \tag{14}$$

Following the technical approach of Mnif et al. (2020), this study measures both the range of the GHE ΔH ≡ max q H(q) - min q H(q) and the width of the multifractal spectrum Δα ≡ max q α(q) - min q α(q) to calculate the level of multifractality, in which a change may occur when those measures differ. In the empirical investigation, the scale range is fixed where $s_{\min}$ = 10 and $s_{\max}$ = (T/4) for MFDFA (Rizvi et al., 2014). *T* shows the length of the series for vaccine stocks.

4.3. Magnitude of Long-Memory (MLM)

The major aim of measuring the MLM is to assess the level of market efficiency. This is also called the index for market inefficiency based on the multifractal dimension. It indicates that the random walk fluctuations include smaller *H*(-5) and larger *H*(+5).

In that vein, the volatilities of returns of selected vaccine stocks are entirely efficient with no long memory and no explosive-type behaviour when MLM = 0.

Therefore, a higher (lower) MLM value refers to a higher (lower) long memory level and a higher (lower) degree of explosive behaviour in the volatility of the returns of vaccine stocks. Following the logical structure of Khuntia and Pattanayak (2020), the efficiency level and the degree of explosive-type behaviour are estimated as depicted in Eq. (15):

$$Magnitude\ of\ Long - memory\ (MLM) = \frac{1}{2}(|h(-5) - 0.5| + |h(5) - 0.5|) \tag{15}$$

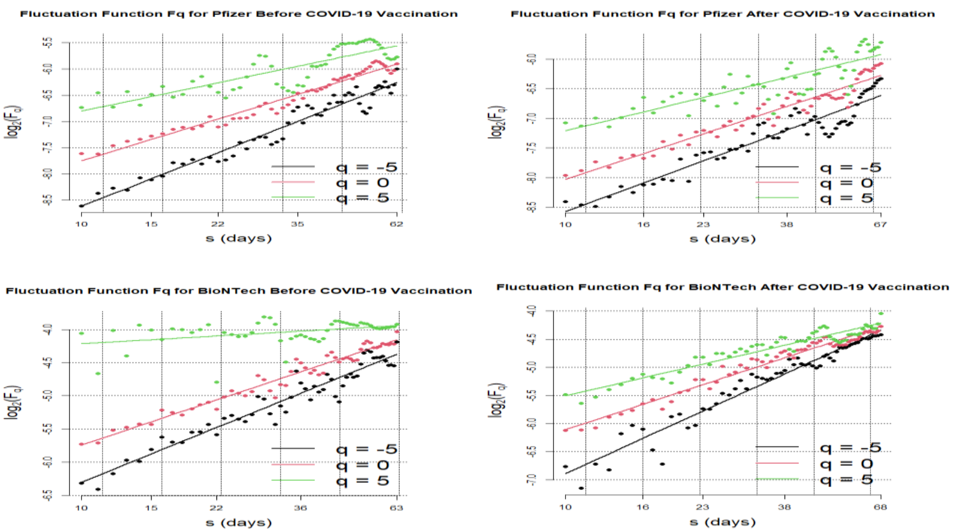
5. Empirical Findings

The first issue is to check whether the multifractal series with a non-normal distribution have various traces. Figs. (2)-(5) show the standard MFDFA findings for the remaining components of the selected vaccine stocks, covering Pfizer, BioNTech, Moderna, Johnson&Johnson, and AstraZeneca. In each figure, the log-log relationship between $F(q)$ and *s* is represented as a clear shape and in a straight line. To test the changes in slopes of h_q, the cored dots for different orders of the exponent are depicted in Fig. 2, where they are ranged between q = 5 (black), q = 0 (red), and q = -5 (green). In that vein, Fig. 2 represents the q^{th}-order Hurst exponent (i.e., h_q), which validates that the traces for h_q are assorted during the COVID-19 pandemic. The fluctuation functions show that the multifractal spectra for the selected vaccine stocks are highly symmetric during the COVID-19 pandemic. This indicates that there are self-similar fractals of vaccine returns. In other words, the vaccine returns have a bearing upon several factors and dimensions and their dependence on past patterns, so this does not allow us to make an accurate prediction of changes in their values over time and thus leads to achieving biased outcomes in the future.

The Hurst exponent is measured in the next step by following $F_q(s)$. Note that the stationary of the time series leads to estimating different settings of the Hurst exponent, such as taking $q = 2$ for the scaling exponent. The figures also comprise the values of the generalised Hurst exponent (H_q) where the values are declining, thus indicating the multifractality in the time fluctuation of the remaining component. The evaluation of *F(q)* versus *q* (represented in Fig. 2) and *H(q)* versus *q* (represented in Fig. 3) leads to select H(q) between H(q = 5) and H(q = -5) since the slopes of vaccine stocks are lent themselves to soft change across the COVID-19 pandemic.

To extend the multifractal dimension, the values of the Renyi exponents $\tau(q)$ and f_α are produced using Eqs. (8)-(14). The estimation results indicate that the monofractal series is linear, whereas the multifractal series shows a non-linear trend. The exponential shape of $\tau(q)$ means that the series exhibits multifractality (Fig 4). In addition, a single-humped shape of the multifractal spectrum f_α indicates that the series is multifractal (Fig. 5).

Figure: 2
Fluctuation Function Before and After the COVID-19 Vaccination



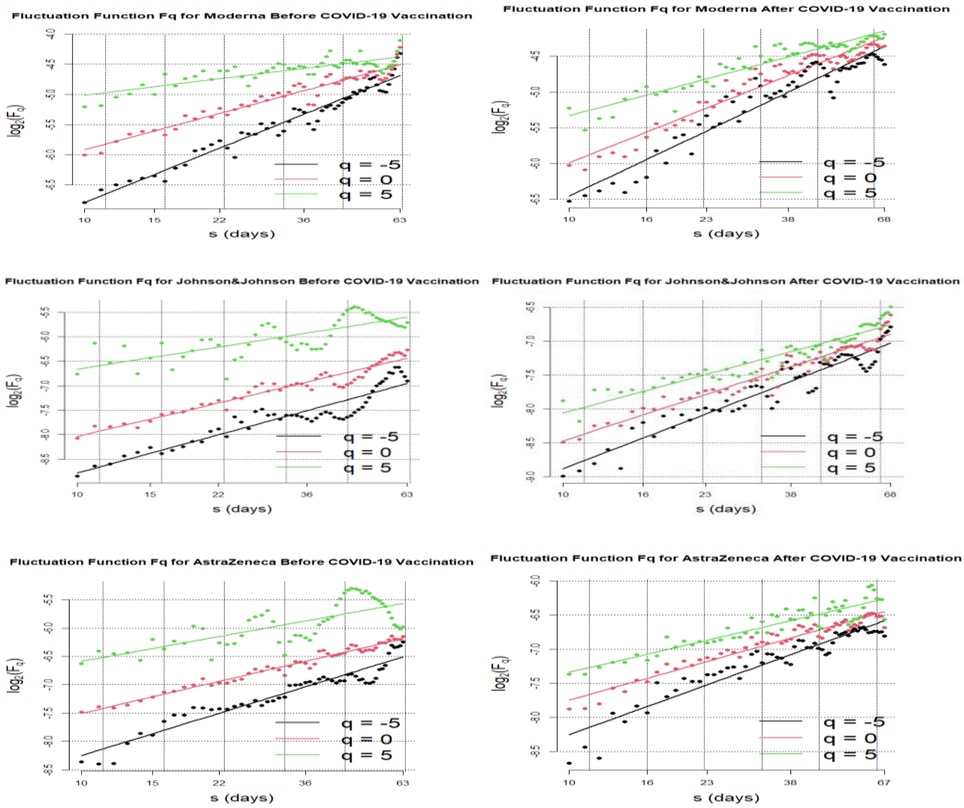
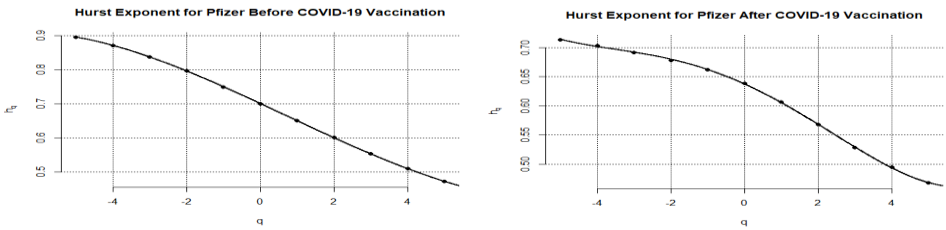


Figure: 3
Hurst Exponent Before and After the COVID-19 Vaccination



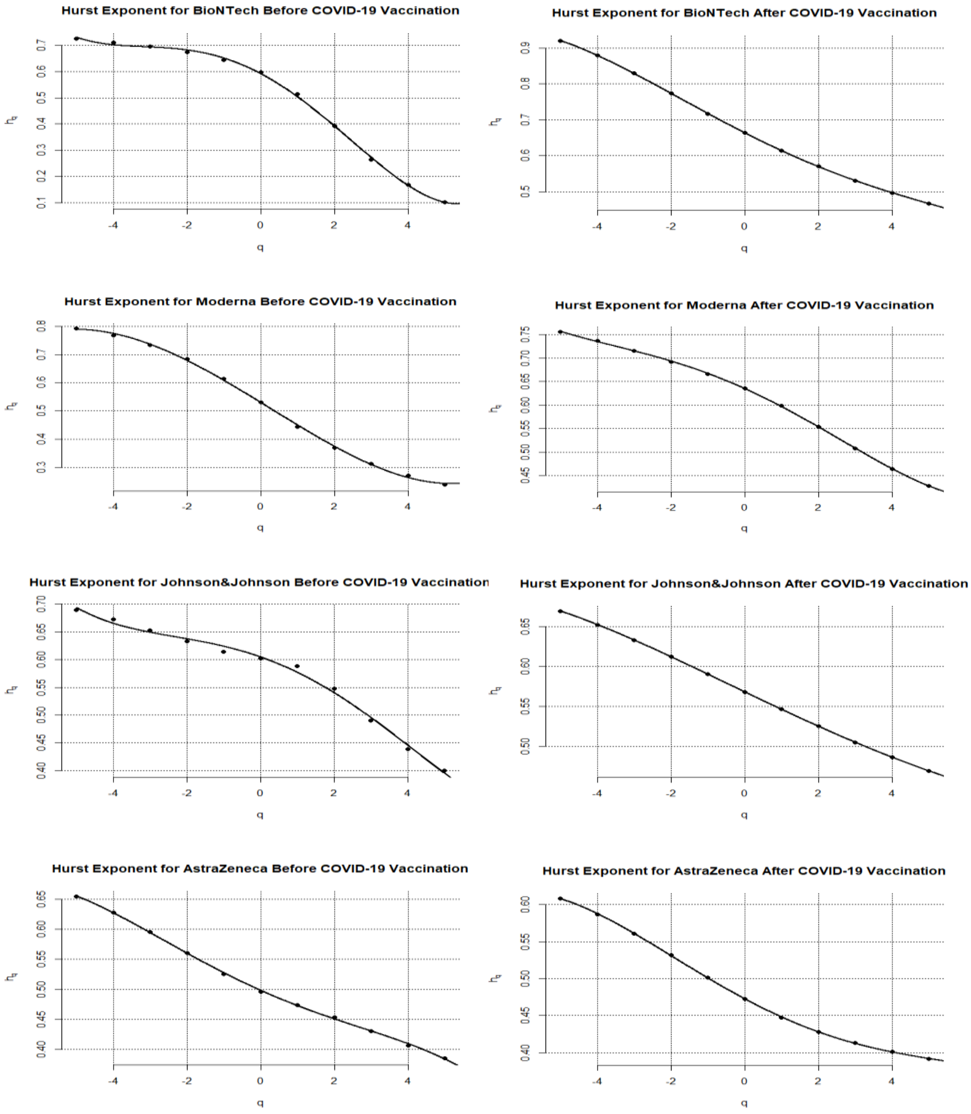


Table 2 summarises the generalised Hurst exponent over the range of $q \in$ [-5, 5] for all vaccine stock indices. Most importantly, the values of $h(q)$ in each vaccine stock have a declining trend; hence, the series is characterised by multifractality in the time fluctuation of the remaining components (Laib et al., 2018a, 2018b). First, the widest range of generalised Hurst exponent $\Delta h(q)$ before the vaccination is for the BioNTech, followed by the Moderna (0.6249 and 0.5528, respectively), referring to the highest levels of multifractality (i.e., least efficient vaccine stocks before the vaccination). In addition, the narrowest range of generalised Hurst exponent $\Delta h(q)$ is in AstraZeneca and Johnson&Johnson (0.2700 and 0.2899, respectively), indicating that these vaccine stocks have the lowest levels of multifractality (i.e., greatest efficiency) before the vaccination. Second, the broadest range of generalised Hurst exponent $\Delta h(q)$ after vaccination is again in BioNTech, followed by the Moderna (0.4530 and 0.3282, respectively), referring to the highest levels of multifractality (i.e., least efficient vaccine stocks after the vaccination). However, the narrowest range of generalised Hurst exponent $\Delta h(q)$ is in Johnson&Johnson and AstraZeneca (0.1998 and 0.2167, respectively), indicating these vaccine stocks have the lowest levels of multifractality (greatest efficiency) after the vaccination.

Table: 2
Generalised Hurst Exponent for -5<q<5

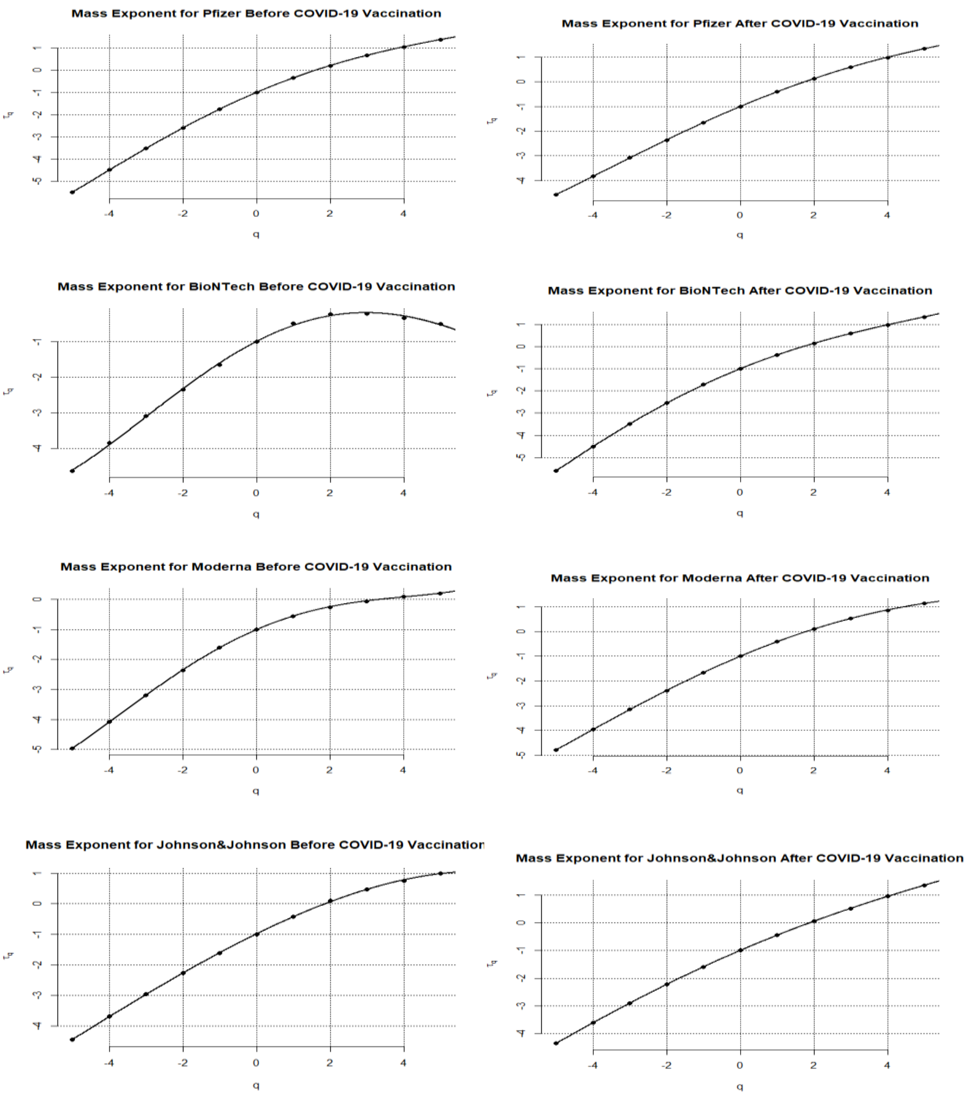
q	Pfizer		BioNTech		Moderna		Johnson&Johnson		AstraZeneca	
	Before	After	Before	After	Before	After	Before	After	Before	After
-5	0.8958	0.7132	0.7265	0.9199	0.7921	0.7562	0.6896	0.6692	0.6550	0.6085
-4	0.8706	0.7030	0.7123	0.8791	0.7676	0.7367	0.6727	0.6523	0.6278	0.5868
-3	0.8379	0.6915	0.6953	0.8294	0.7329	0.7154	0.6531	0.6330	0.5957	0.5611
-2	0.7970	0.6782	0.6740	0.7733	0.6833	0.6922	0.6325	0.6121	0.5605	0.5321
-1	0.7500	0.6616	0.6444	0.7165	0.6148	0.6664	0.6143	0.5902	0.5257	0.5015
0	0.7008	0.6387	0.5972	0.6634	0.5304	0.6358	0.6022	0.5682	0.4962	0.4724
1	0.6513	0.6067	0.5151	0.6148	0.4440	0.5982	0.5881	0.5464	0.4741	0.4476
2	0.6016	0.5676	0.3922	0.5703	0.3698	0.5539	0.5476	0.5253	0.4535	0.4280
3	0.5535	0.5285	0.2649	0.5304	0.3128	0.5074	0.4899	0.5052	0.4300	0.4129
4	0.5192	0.4950	0.1677	0.4958	0.2706	0.4644	0.4386	0.4864	0.4062	0.4011
5	0.4733	0.4682	0.1016	0.4669	0.2393	0.4280	0.3997	0.4694	0.3850	0.3918
Δh	*0.4225*	*0.2450*	*0.6249*	*0.4530*	*0.5528*	*0.3282*	*0.2899*	*0.1998*	*0.2700*	*0.2167*

Table: 3
Multifractal Spectrum (α) from Upper to Lower Probabilities

α	Pfizer		BioNTech		Moderna		Johnson&Johnson		AstraZeneca	
	Before	After	Before	After	Before	After	Before	After	Before	After
1	0.9966	0.7540	0.7833	1.0831	0.8901	0.8342	0.7572	0.7368	0.7638	0.6953
2	0.9687	0.7375	0.7633	1.0282	0.8717	0.8006	0.7315	0.7102	0.7241	0.6639
3	0.9197	0.7181	0.7379	0.9416	0.8321	0.7618	0.6943	0.6848	0.6661	0.6191
4	0.8440	0.6948	0.7036	0.8301	0.7518	0.7180	0.6507	0.6340	0.5953	0.5627
5	0.7500	0.6616	0.6444	0.7165	0.6148	0.6664	0.6143	0.5902	0.5257	0.5015
6	0.6513	0.6067	0.5151	0.6148	0.4440	0.5982	0.5881	0.5464	0.4741	0.4476
7	0.5519	0.5285	0.2693	0.5258	0.2956	0.5096	0.5071	0.5042	0.4329	0.4084
8	0.4573	0.4503	0.0103	0.4506	0.1988	0.4144	0.3745	0.4650	0.3830	0.3827
9	0.3803	0.3945	-0.1239	0.3920	0.1440	0.3354	0.2847	0.4300	0.3348	0.3657
10	0.3207	0.3610	-0.1628	0.3513	0.1141	0.2824	0.2441	0.4014	0.3002	0.3546
Δα	*0.6759*	*0.3930*	*0.9461*	*0.7318*	*0.7760*	*0.5518*	*0.5131*	*0.3354*	*0.4636*	*0.3407*

Furthermore, Table 3 depicts the multifractal spectrum (α) from upper and lower probabilities before and after the vaccination. Considering the generalised Hurst exponent $\Delta h(q)$, the degree of q is mostly higher than 0.5, which refers that the selected vaccine stocks show persistent behaviour (positive/negative), meaning that any change (positive/negative) before the vaccination would probably be followed by the same (positive/negative) change after the vaccination. Those estimated values indicate that they are subjected to predictability and thus are represented by the evidence of vaccine stocks’ inefficiency after the vaccination, which suggests that trend trading strategies could lead to a burst of abnormal profits in those selected vaccine stocks during the given time dimension (Caporale et al., 2018).

Figure: 4
Mass Exponent Before and After the COVID-19 Vaccination



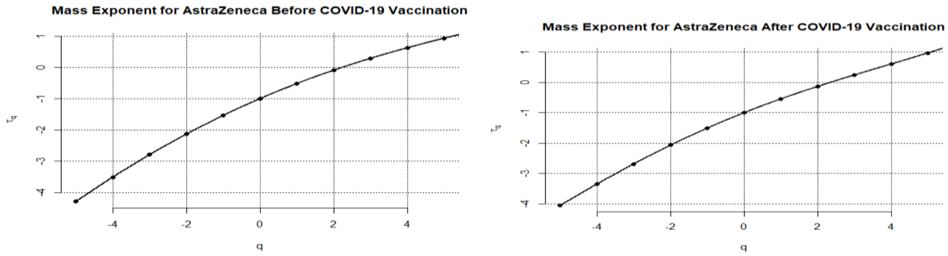
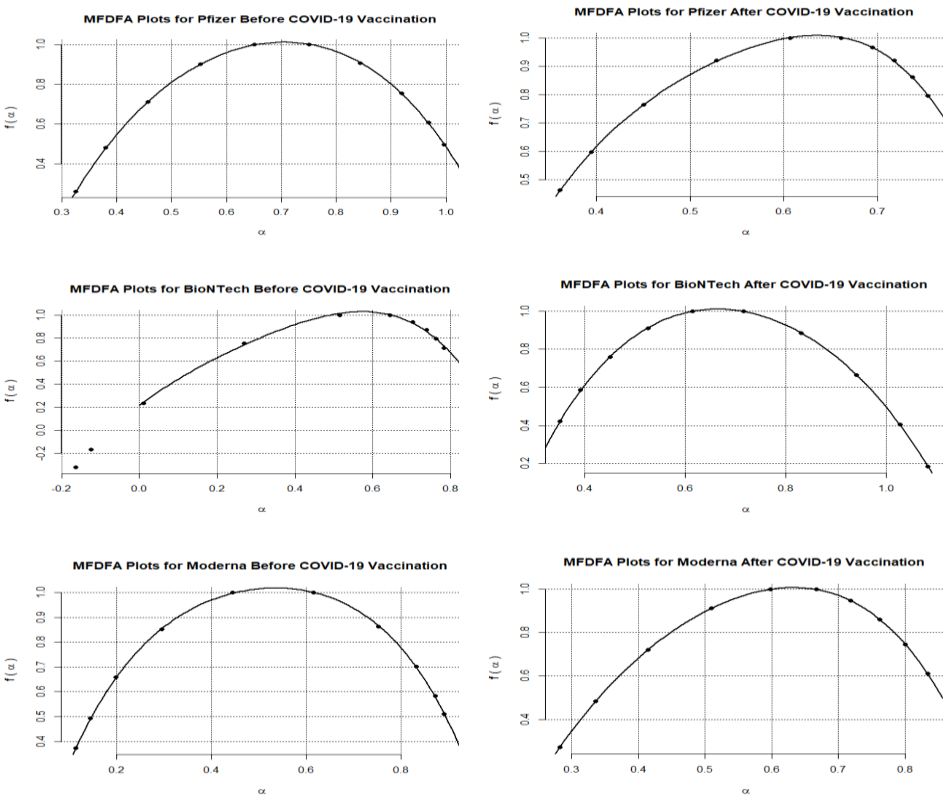
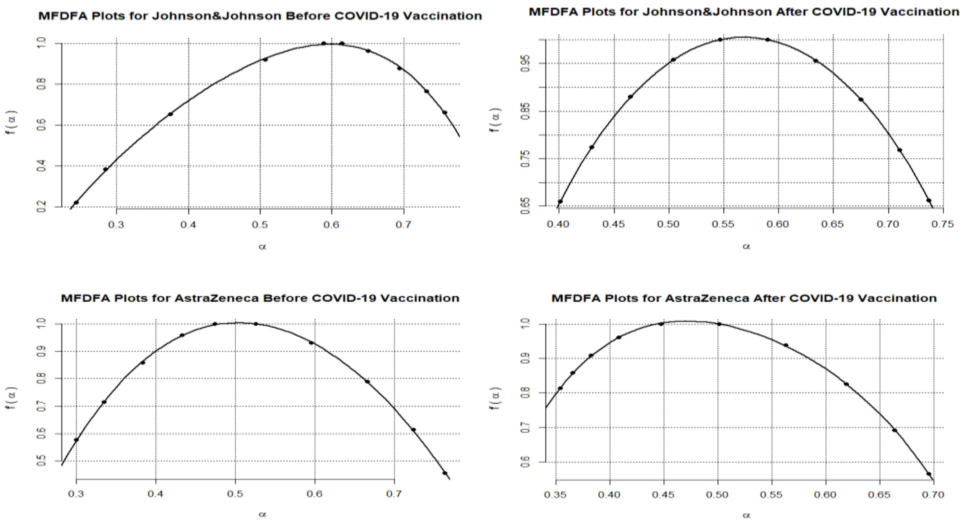


Figure: 5
MFDFA Plots Before and After the COVID-19 Vaccination





The multifractality results are summarised in Table 4. Although the estimated values of the general Hurst exponent document that vaccine stocks have persistent behaviour and are predictable with evidence of inefficiency during the given period, the presence of herd behaviour and the level of market efficiency have differential patterns across the selected vaccine stocks. Primarily, the width of the multifractal spectrum Δα refers to the expansion of this weighted average being in line with the increase of multifractality (Lu et al., 2013). Regarding the change in multifractal spectrum average from pre-vaccination to post-vaccination period, the estimations show that the multifractality increased for BioNTech, Moderna, and Johnson&Johnson.

Moreover, the presence of herd investing in vaccine stocks is also documented in Table 4. A bulk of studies use the fractal theory, in which the roots of this theory trace to the Hausdorff topology, to assess the change in herding biases in financial markets. In this sense, the fractal dimension (*d*) is used to analyse the shift in herding behaviour across different time horizons. The estimated fractal dimension (d) values refer to the herding behaviour that can be put forward for each vaccine stock and increased for BioNTech and Moderna during the post-vaccination period. Besides, the ranking values of fractal dimension (*d*) provide a way to assess the weight of herding behaviour that those two vaccine stocks are faced with an increase in it during the post-vaccination period. Considering the ranking of estimated values of fractal dimension (*d*), while Pfizer and Johnson&Johnson have the highest degree (1.3045 and 1.4247, respectively) of herding behaviour before the vaccination, BioNTech and Moderna became the highest degree (1.3218 and 1.3859, respectively) of herd investing after the vaccination.

Finally, the estimated values of the MLM (inefficiency) index provide that the selected vaccine stocks are inefficient to various degrees. The highest level of MLM (inefficiency) index is attributed to BioNTech before and after the vaccination (0.3125 and 0.2265, respectively). However, the MLM (inefficiency) index did not increase during the given periods, even if the market inefficiency is given within various degrees.

Table: 4
Multifractality Results

		Δh	Δα	Hurst average	Multifractal spectrum average (α)	Fractal dimension (d)	MLM (inefficiency) index	Ranking
Pfizer	Before	0.4225	0.6759	0.6955	0.6841	1.3045	0.2113	1
	After	0.2450	0.3930	0.6138	0.5907	1.3862	0.1225	3
BioNTech	Before	0.6249	0.9461	0.4992	0.4141	1.5008	0.3125	5
	After	0.4530	0.7318	0.6782	0.6934	1.3218	0.2265	1
Moderna	Before	0.5528	0.7760	0.5234	0.5157	1.4766	0.2764	3
	After	0.3282	0.5518	0.6141	0.5921	1.3859	0.1641	2
Johnson&Johnson	Before	0.2899	0.5131	0.5753	0.5447	1.4247	0.1449	2
	After	0.1998	0.3354	0.5689	0.5703	1.4311	0.0999	4
AstraZeneca	Before	0.2700	0.4636	0.5099	0.5200	1.4901	0.1350	4
	After	0.2167	0.3407	0.4858	0.5002	1.5142	0.1084	5

6. Conclusion

This study analysed the level of market efficiency and herd investing in the selected vaccine stocks, including Pfizer, BioNTech, Moderna, Johnson&Johnson, and AstraZeneca, using the generalised Hurst exponent (GHE) and MLM (inefficiency) index as a way of measuring fractality through the multifractal detrended fluctuation approach (MFDFA) comparatively for the pre-vaccination and post-vaccination periods. The primary concern of this paper was to assess whether the vaccine stocks have become more prone to an increase in herd investing before and after the vaccination process of the coronavirus pandemic.

First, the estimation results of the generalised Hurst exponent documented that the vaccine stocks were multifractal during the sample period. However, herd investing and market efficiency fluctuated from the pre-vaccination to the post-vaccination period. Accordingly, the change in the value of the multifractal spectrum average showed that the extant multifractality increased for BioNTech, Moderna, and Johnson&Johnson from the pre-vaccination to post-vaccination period. In other words, the vaccination process increased herd biases in those vaccine stocks and inefficiency.

Furthermore, the fractal dimension (*d*) was measured for each vaccine stock to assess the change in herd investing during the coronavirus outbreak. The estimated fractal dimension (d) values showed that BioNTech and Moderna encountered an increase in multifractality from pre-vaccination to post-vaccination. In addition, the ranking of fractal dimension (*d*) values documented that Pfizer and Johnson&Johnson were confronted with the highest degree of herd behaviour (1.3045 and 1.4247, respectively) for the pre-vaccination period. Still, BioNTech and Moderna became the highest degree (1.3218 and 1.3859, respectively) of herd investing after the vaccination.

Moreover, the MLM (inefficiency) index's estimated values provide that selected vaccine stocks are inefficient to various degrees. The highest value of the MLM (inefficiency) index was attributed to BioNTech before and after the vaccination (0.3125 and 0.2265, respectively). However, the MLM (inefficiency) index did not increase during the given periods, even if the market inefficiency is given within various degrees.

All in all, these results may provide critical knowledge and insights to stock dealers for a future period of selected top vaccine stocks in terms of their efficiency and herding biases and thus help them to analyse their performance for mild-effective periods of the COVID-19 pandemic. Potential future studies may also consider the ways and factors for alleviating the expansion of herding biases and inefficiency in vaccine stocks, along with applying appropriate financial instruments.

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