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The Impact of COVID-19 on BRICS and MSCI Emerging Markets Efficiency: Evidence from MF-DFA

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Abstract: This study examines the response of the BRICS and MSCI emerging stock market indices to the COVID-19 outbreak. For this purpose, this study uses a multifractal detrended fluctuation analysis (MF-DFA) to investigate the market efficiency dynamics of these indices and then ranks them based on their market efficiency. Overall, our results indicate that the returns from all the stock indices exhibit long-range correlations, implying that these markets are not weak-form efficient. Specifically, China showed the highest level of multifractality (i.e., inefficiency), which can be attributed to its highly volatile market structure. Using a subsample analysis, we further explore the impact of COVID-19 on these markets' efficiency by dividing the dataset into pre- and post-COVID periods. The findings indicate that COVID-19 adversely affected the efficiency of all the indices. Surprisingly, improvement in the Chinese market's inefficiency was witnessed, which can be attributed to the prompt and effective measures (i.e., timely imposition of health-related measures such as lockdowns and resident quarantines to contain COVID-19 and financial packages designed to curtail the economic meltdown) introduced by the Chinese government. The findings of this study may help investors, policymakers and regulators in refining their financial and policy decisions according to the new efficiency levels of these markets.

Keywords: market efficiency; econophysics; BRICS; COVID-19; MF-DFA; generalized Hurst exponents

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1. Introduction

The occurrence of epidemics is not a new phenomenon in the history of the world. These epidemics or pandemics have shown extremely harsh impacts in all spheres of life, not just in health. Recently, the most horrifying pandemic of the century, named COVID-19, greatly affected all aspects of life and thus is considered a "once-in-a-century pathogen" due to its devastating impacts. The 1% fatality rate of COVID-19 is more severe than influenza and is comparable with the 1857 influenza pandemic and the 1918 Spanish flu. The exponential spread rate of COVID-19 is also another factor that makes it more severe and difficult to control. Apart from physical damage to health and lives, it has shown dreadful impacts on economies globally.

The world faced severe economic turmoil due to COVID-19 as it reduced working hours and increased unemployment associated with worldwide lockdowns, which had a direct impact on economic activities. Several studies investigated the consequences of COVID-19, for instance, the immediate effects of COVID-19 on individual firms [1] and the impacts of COVID-19 in the long run [2]. The pandemic altered household consumption behaviours significantly [3], where labour market activities and employment have been severely affected by the outbreak [4]. Hence, this entire scenario has directly or indirectly shown the adverse effects in all spheres of life around the world.

With the advent of the COVID-19 pandemic, the question regarding the validity of the efficient market hypothesis (EMH) in financial markets resurfaced. A lot of the literature was dedicated to investigating the impact of COVID-19 on stock markets [5–7]. Ashraf [8] showed that announcements of social distancing by governments to prevent COVID-19 deteriorated economic activity and led to the poor performance of stock markets across 77 countries. Baker et al. [9] claimed that among all other infectious outbreaks in the past (1918–1919, 1957–1958 and 1968), COVID-19 proved to be the most powerful pandemic, showing historic adverse effects on the US stock markets. Government restrictions on commercial activities due to social distancing are the unprecedented explanation for the US stock markets' severe reaction to COVID-19. However, there are studies [10] that report mixed or positive impacts of COVID-19. Hence, the above-mentioned literature suggests that the impact of COVID-19 on financial markets is a reality that must be examined carefully. Additionally, Lekhal and Oubani [11] tested the notion of the Adaptive Market Hypothesis (AMH) and stated that the level of market efficiency is not static as claimed by EMH, but it is bound to the prevailing market conditions. Though the importance of EMH as an honourable theory cannot be refuted, the validity of EMH still needs to be established. Hence, finding out the impacts of COVID-19 on the efficiency of financial markets is very crucial and relevant. To explore this phenomenon, this study investigates the impacts of the COVID-19 pandemic on BRICS stock markets.

The unique patterns of BRICS stock markets such as high volatility, autocorrelation and specifically long-horizon returns make these markets distinctive from other world markets. The similar characteristics of BRICS tempted these economies to share a stronger comprehensive economic, political, cultural and financial cooperation. Xu and Lien [12] stated that BRICS evolved as one of the most advanced emerging economies over the last few decades. During the COVID-19 pandemic, most emerging economies experienced the most unprecedented increase in outflows as investors shifted huge amounts of capital from emerging markets to safe-haven assets [13]. Additionally, many COVID-19 correlated events such as lockdowns, government interventions [14] and the launch of vaccines [15] significantly impacted the global stock markets. As a result, significant distortions are expected to occur in the BRICS stock markets' efficiency. Moreover, COVID-19 erupted in China, so Chinese financial markets can be termed the epicentre of financial contagion. Therefore, the impact of COVID-19 on the Chinese stock market and on BRICS cannot be undermined. Hence, investigating the market dynamics of this prominent economic collaboration of BRICS during the COVID-19 era needs special attention. For this purpose, we investigate the efficiency of the BRICS stock markets. Further, MXEF is used as the benchmark index for comparing the efficiency levels of the BRICS stock markets.

The EMH is based on the notion of the random walk hypothesis (RWH) proposed by Bachelier [16]. The notion behind RWH states that the information is freely available, which is immediately incorporated into the security prices [17]. This means that future stock prices are independent of past events, and thus, no prediction can be performed. However, the econophysics literature suggests that the stock markets are complex entities where the asset prices possess several fundamental properties including long-term correlation [18], fat tails [19], volatility clustering [20], fractal and multifractal properties [21] and chaos [22]. Therefore, to examine the complex nature of financial markets, fractal analyses such as MF-DFA are widely used [23]. The advantage of using MF-DFA is that it allows for sequentially ranking individual markets on the basis of market efficiency [24].

We contribute to the existing body of literature by investigating the multifractal behaviour of BRICS and MXEF returns in the context of COVID-19. This study further ranks the indices according to their level of efficiency in both pre- and post-COVID-19 periods, specifically elaborating on the consequences of the COVID-19 outbreak for the ranking of market efficiency. From a methodological perspective, our study extends the work of Günay [25] by specifically examining the impact of COVID-19 on market efficiency.

The key findings of this study indicate that the returns from BRICS stock indices exhibit long-range correlations, implying that these indices are not weak-form efficient. However, the indices are found to move toward efficiency over time. In addition, it is evident that the impact of COVID-19 on the BRICS and MXEF indices is not a myth.

The rest of this paper is organized as follows. Section 2 describes the data and research methodology. Section 3 summarizes empirical results and Section 4 outlines the ranking of market efficiency. Section 5 provides the conclusions and policy implications.

2. Data and Research Methodology

The daily closing prices of the BRICS and MXEF indices were obtained from Bloomberg. The stock indices used in this study include the BOVESPA Index of Brazil (IBOVESPA), MOEX Index of Russia (IMOEX), S&P BSE Sensex index of India (SENSEX), SSE Composite Index of China (SHCOMP) and JSE All Share index of South Africa (JALSH). The fourth column of Table 1 indicates the beginning dates for each index, which continue until 30 July 2020. The total number of observations is stated in the last column.

Table 1. The BRICS and MXEF indices.

Country/Index	Market Capitalization (USD)	Index	Beginning Date
Brazil	988.37 billion	IBOVESPA	3 January 1994
Russia	694.74 billion	IMOEX	22 September 1997
India	2.60 trillion	SENSEX	1 January 1998
China	12,214.47 trillion	SHCOMP	19 December 1990
South Africa	1.05 trillion	JALSH	2 July 1995
MXEF	5.73 trillion	MXEF	1 December 1990

Note: BRICS market capitalization is based on the most recent data (2020) available from The World Bank [26]. Data for MXEF (as of 30 September 2022) were sourced from MSCI [27].

The MXEF is developed by MSCI and comprises 24 emerging economies, such as Brazil, the Czech Republic, China, Egypt, Greece, Indonesia, Malaysia, Poland, Qatar, Taiwan, South Africa and the United Arab Emirates. MSCI indices are considered robust since they have 99.6% accuracy in index production [28]. It is common practice for various studies to consider MSCI indices as benchmarks, for example [28–30]. Since BRICS is a bloc of emerging economies, the performance of this bloc is comparable to the MXEF index, which reflects the cumulative performance of emerging economies throughout the world. Hence, the MXEF is considered the benchmark for comparing the performance of the BRICS stock markets.

2.1. Time Series Analysis of Stock Markets

In the first step, stock market returns are calculated, and then multifractal detrended fluctuation analysis (MF-DFA) is applied to the stochastic component of the financial return series.

2.1.1. Stock Market Returns

Table 2 presents the descriptive statistics for the BRICS and MXEF stock returns. The mean returns and standard deviations for all indices varied widely. The highest mean returns were observed for the Brazilian stock index, i.e., 0.001093, whereas the lowest was observed for South Africa at 0.000476. It is also evident that the mean returns from BRICS outperformed the benchmark MXEF mean returns (0.000289) over the whole sample.

Table 2. Descriptive statistics.

Index	Brazil	Russia	India	China	South Africa	MXEF
Mean	0.001093	0.000909	0.000568	0.000739	0.000476	0.000289
Std. Dev.	0.021981	0.024408	0.014992	0.024196	0.012151	0.011215
Skewness	0.831892	0.889429	−0.083120	12.17468	−0.389831	−0.403955
Kurtosis	16.07679	22.37519	8.299817	494.5483	6.30476	7.60328
JB	74,045.00	125,000.00	16,779.00	76,248,000	10,938.00	20,032.00
Prob.	0.000	0.000	0.000	0.000	0.000	0.000

Note: Std. Dev. refers to standard deviation and JB indicates the Jarque–Bera test.

The Russian stock market returns showed the highest standard deviation (0.024408), while South Africa reported the lowest (0.012151). The return series for the BRICS and MXEF stock indices showed a significant level of skewness and kurtosis. The Brazilian, Russian and Chinese return series were positively skewed, while those for India and South Africa were negatively skewed. The benchmark MXEF index showed negative skewness as well. The kurtosis values for all indices showed sharp peaks. The Jarque–Bera statistics for BRICS and MXEF returns reported smaller p-values and greater chi-square values, implying non-normality in all the return series.

2.1.2. Multifractal Detrended Fluctuation Analysis (MF-DFA)

Günay [25] explored the performance of the multifractal model of asset returns (MMAR), which was developed by Mandelbrot et al. [31] as an alternative to the ARCH family models. After investigating the performance of GARCH, EGARCH, FIGARCH, MRS-GARCH and MMAR in identifying the characteristics of long memory, trading time and fat tails in four emerging markets from Croatia, Greece, Poland and Turkey, the study concluded that the MMAR is superior to the other traditional models [25]. In this paper, we utilize the MF-DFA method to investigate the efficiency of BRICS and MXEF stock market indices. The MF-DFA is the most powerful technique for detecting multifractality in time series [32]. It picks the average volatility in the time series for each interval as a statistical point that is further used to calculate volatility functions. It is then used to determine the generalized Hurst exponents based on the power law of volatility functions [33]. The prominent advantage of the MF-DFA technique over other approaches is its ability to detect long-term correlations in non-stationary time series. The key steps and formulas underlying the analysis in this technique are given below.

Let $r(i)$ for $i = 1, \ldots, N$, be a possibly non-stationary time series of stock market returns, where N denotes the series length. The first step in MF-DFA includes constructing the 'profile', $Y(j)$, using integration after subtracting from the time series, $r(i)$, its average $\bar{r}$ [32].

$$Y\ (j)\ \equiv \sum_{i=1}^{j} (r(i) - r),\ i = 1,\ \ldots,\ N \tag{1}$$

In the second step, the $Y(j)$ profile is divided into $N_s \equiv \text{int}\ (N/s)$ non-overlapping segments with equal lengths. One can ignore the short part of the profile $Y(j)$ at the end, and the sub-division is realized starting from the opposite end. Consequently, a total of $2N_s$ segments are obtained.

The third step in MF-DFA includes computing the local trend for each of the $2N_s$ segments with the least-squares fit of the series using Equation (2);

$$F^2(s,v) = \frac{1}{s} \sum\nolimits_{j=1}^{s} \{Y[(v-1)\ s + j] - y_v\ \ (j)\}^2 \tag{2}$$

For each segment v, $v = 1, \ldots, N_s$ and

$$F^2(s,v) = \frac{1}{s} \sum\nolimits_{j=1}^{s} \{Y[N - (v - N_s)\ s + j] - y_v\ \ (j)\}^2 \tag{3}$$

For $v = N_{s+1}, \ldots, 2N_s$, where $y_v(j)$ is the polynomial fit in segment v.

The fourth step in MF-DFA involves averaging over all the segments obtained from the second step to obtain the qth-order fluctuations.

$$F_q(s) = \{\frac{1}{2N_s}\sum_{v}^{2N_s}[F^2(s,v)]^{\frac{q}{2}}\}^{\frac{1}{q}} \quad \text{If } q \neq 0 \tag{4}$$

and

$$F_q(s) = \{\frac{1}{4N_s}\sum_{v}^{2N_s} ln[F^2(s,v)]\} \quad \text{If } q = 0 \tag{5}$$

The parameter q helps to distinguish between the segments with small and large fluctuations. A negative value of the q parameter enhances the small fluctuations, whereas a positive value enhances the large fluctuations. The appropriate selection of parameters s and q is important while using MF-DFA as the fluctuation functions $F_q(s)$ are depended on the choice of segment size s and the qth power. An analysis was performed by taking three different scenarios, i.e., $q = -10{:}10$, $q = -5{:}5$ and $q = -2{:}2$. The resulting generalized Hurst exponents (GHEs) in the middle of the moments were identical. This implies that our analysis is insensitive to the selection of different qs. Hence, the market inefficiency calculated in all three scenarios turns out to be the same (see Appendix A). However, these findings indicate that the resulting fluctuation functions at $q = -2{:}2$ provide the best fit. Hence, we selected $q = -2{:}2$ for our analysis and interpreted the results at $q = 1$, using the conservative approach as recommended by [34–36].

Moreover, MF-DFA is a technique that aims at exploring the long-range correlations and persistence in the time series. In DFA, s changes as n^2, i.e., 2, 4, 8, 16 and so on. Usually, in finance, the scale range 2~64 is used for capturing the short-range dynamics, whereas 64~256 is used for medium-range and 256~1024 and above for long-range dynamics [37]. An analysis was performed by changing the different ranges of s (i.e., $s = 8{:}512$, $s = 8{:}1024$ and $s = 8{:}2048$) in one of our data series IBOV, and the market inefficiency was measured using the $GHE_{q=1}$ values (see Appendix B). It was evident that an enhanced market inefficiency was seen when we used smaller s (highest in the case of $s = 8{:}512$). In our study, we are interested in finding out the long-range fluctuations in the BRICS and MXEF indices; therefore, we used $s = 8{:}2048$ in our analysis.

The final step includes determining the scaling exponent in the fluctuation function for any fixed q and obtaining the relationship between $F_q(s)$ and s. If $F_q(s)$ is considered the power law, the series is in the log–log scale for that particular q:

$$F_q(s) \propto s^{h_q} \tag{6}$$

where the exponent h_q is known as the Hurst exponent. The Hurst exponents are used to calculate the market efficiency or inefficiency [38,39]. A Hurst exponent with a value that ranges between 0.5 and 1 implies the existence of a positive correlation (persistent behaviour). It is characterized by long memory effects, which occur regardless of the timescale. A value closer to 1 indicates the presence of large and abrupt changes, whereas a value between 0 and 0.5 indicates the presence of a negative correlation, which is known as anti-persistent behaviour [40]. Anti-persistence refers to covering less distance by reverting itself more frequently than any random process does. A value of H equal to 0.5 ($q = 0$) reflects a Brownian time series, or it can be described as a classical random walk [40,41]. Generally, the series is characterized by multifractality if the exponent h_q depends on q, and it monotonically decreases as q increases. However, when h_q is not dependent on q, the series is termed monofractal [32] and vice versa.

The h_q derived from MF-DFA can also be expressed as a function of the Renyi exponent,

$$\tau(q){:}\ \tau(q) = qh_q - 1 \tag{7}$$

3. Empirical Results

3.1. Overview of BRICS Stock Market Efficiency

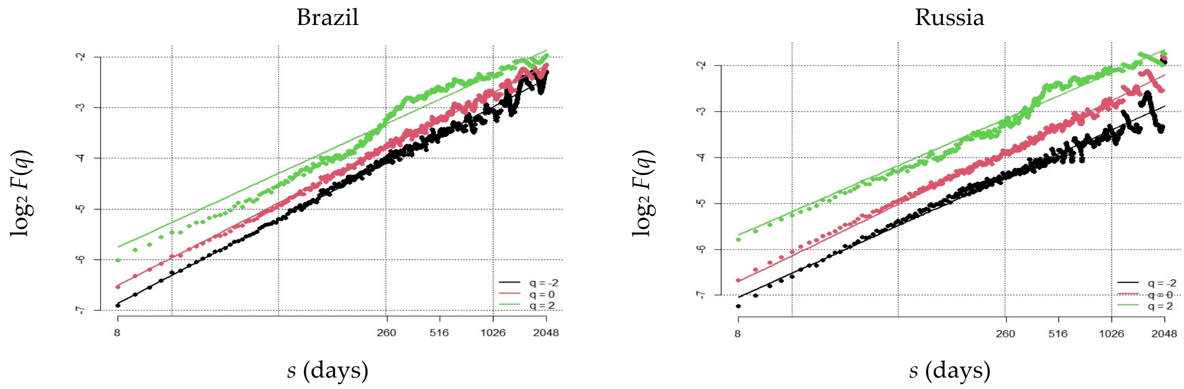
In Table 3, we present the generalized Hurst exponents h_q for BRICS and emerging stock market indices. The values show moderate variation in the h_q as q moves from -2 to 2. In general, it is evident that h_q is a decreasing function, which implies the presence of multifractality in all the time series. h_q continues to decline as q moves from -2 to 2, implying that the stock markets under study became relatively more efficient with the passage of time.

Table 3. Generalized Hurst exponents for BRICS and MXEF stock indices and their ranges over $q \in [-2, 2]$.

	Brazil	**Russia**	**India**	**China**	**South Africa**	**MXEF**
-2	0.5545	0.5207	0.5848	0.7507	0.5306	0.6109
-1	0.5507	0.541	0.5743	0.7019	0.5273	0.5909
0	0.5429	0.5634	0.5602	0.6766	0.5202	0.5701
1	0.5227	0.5511	0.539	0.6442	0.5045	0.5467
2	0.4860	0.5059	0.5115	0.5836	0.4790	0.5191

The values of the Hurst exponents for all BRICS indices change over each next level of q. For example, in the case of Brazil and South Africa, a positive autocorrelation is evident for GHE values ranging from $q = -2$ to 1, indicating persistence. Moreover, at $q = 2$, the value for Brazil and South Africa drops from 0.5, which implies anti-persistent behaviour. However, in the case of Russia, India, China and the emerging markets index, persistent behaviour is consistent from $q = -2$ to $q = 2$.

Figure 1 depicts the scaling behaviour of the fluctuation functions for the BRICS and MXEF return series, plotted between the log–log plots for $F_q(n)$ and scale s (days). The Hurst exponents h_qs are calculated with the help of $F2$. The existence of scaling for any q are pointed out using the fluctuation functions, which represent a straight line in log–log scales and are well-fitted.



(**a**) (**b**)

Figure 1. *Cont.*

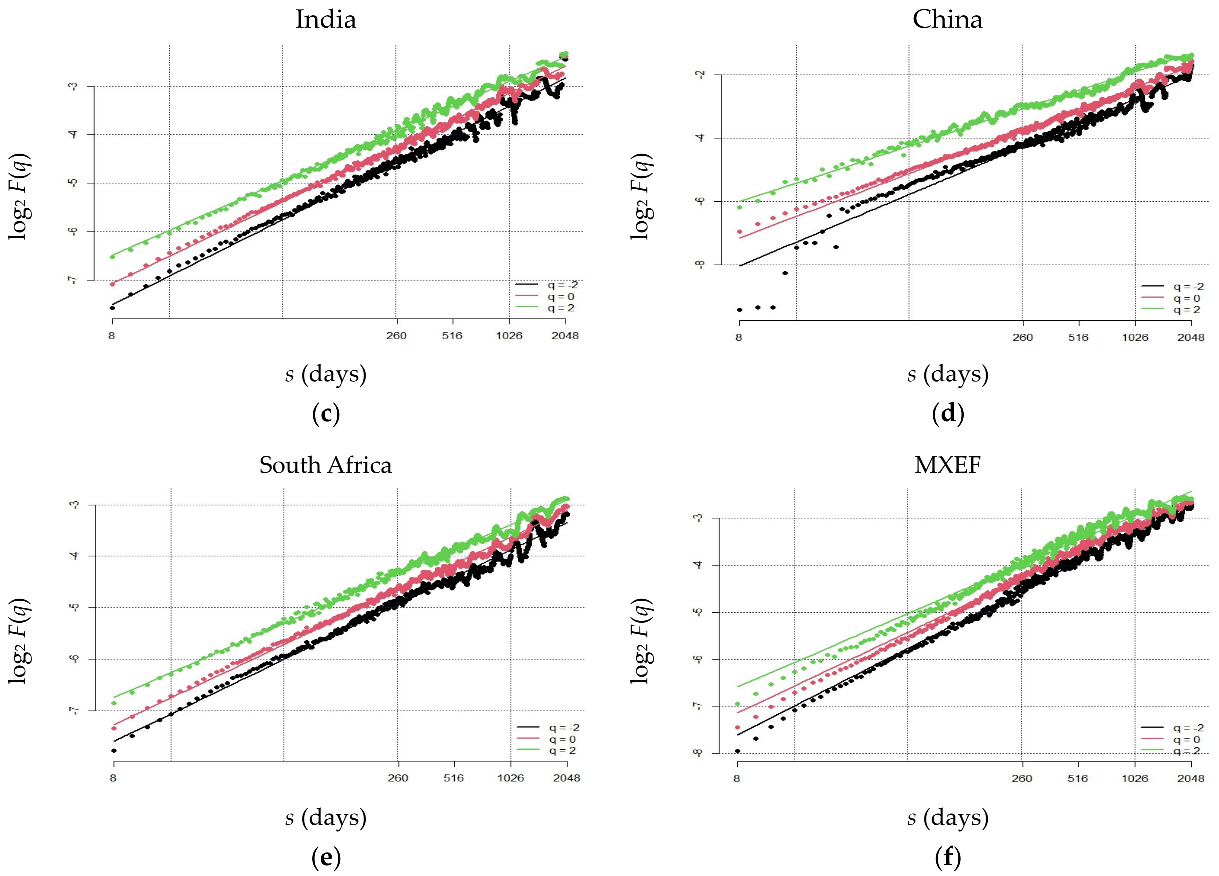


Figure 1. Scaling behaviour of the fluctuation function. The y-axis refers to $\log_2 F(q)$ while x-axis denotes s (days). Panels (**a**–**e**) denote each of the BRICS index, while Panel (**f**) indicates the MXEF.

Figure 2 shows the relationship between the generalized Hurst exponent h_q and q for the BRICS and MXEF indices. If h_q is constant for all q, the series is termed monofractal. We can see that the h_qs are q-dependent and are decreasing from right to left as q moves from -2 to 2. This confirms the existence of multifractality in the time fluctuations for all the series.

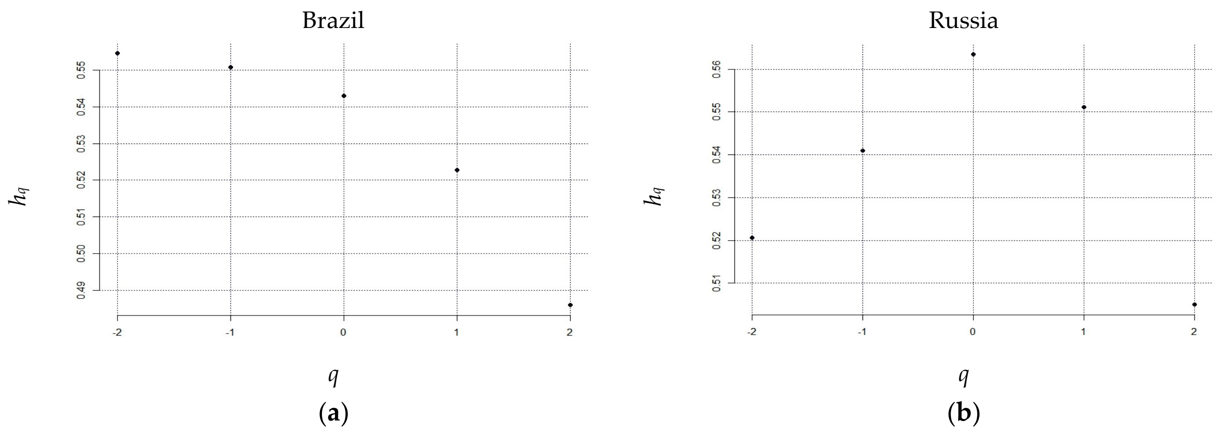


Figure 2. *Cont.*

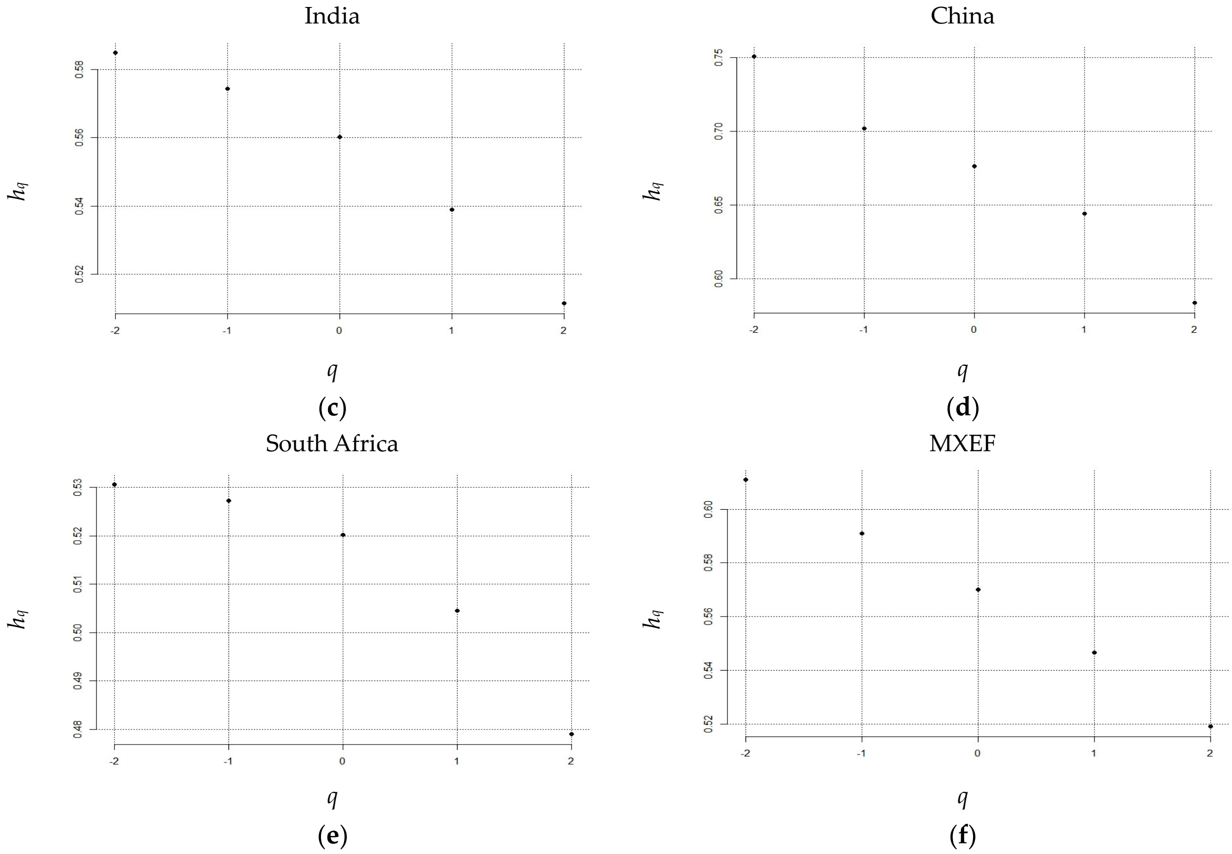


Figure 2. Relationship between the Hurst exponents and qs. The y-axis refers to h_q while x-axis denotes q. Panels (**a**–**e**) show each of the BRICS index, while Panel (**f**) represents the MXEF.

Figure 3 highlights the Renyi exponents for the BRICS and MXEF indices. The h_qs resulting from MF-DFA can also be expressed as a function of the Renyi exponent, which represents the presence of multifractality in any time series. If $\tau(q)$ is constant, the series is known as monofractal, and vice versa.

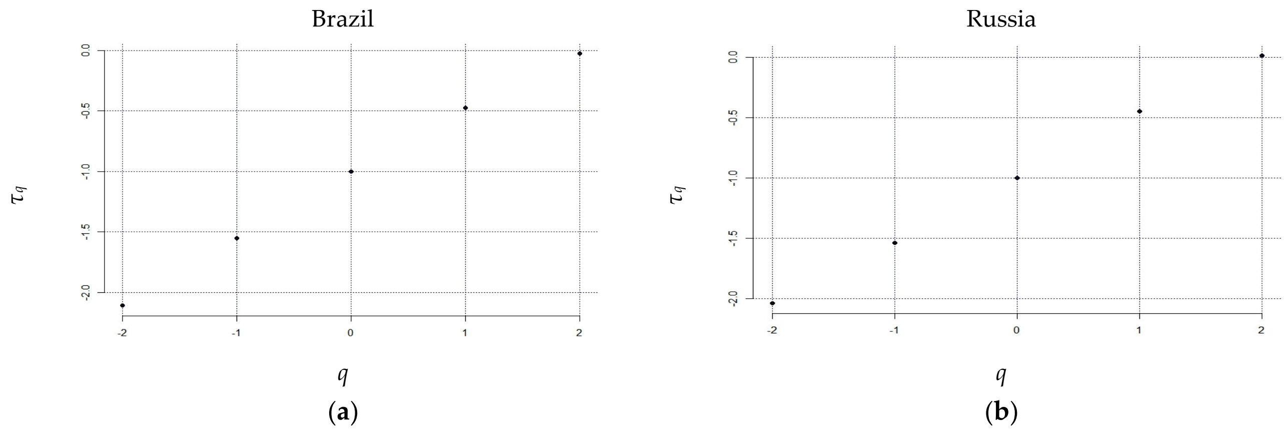


Figure 3. *Cont.*

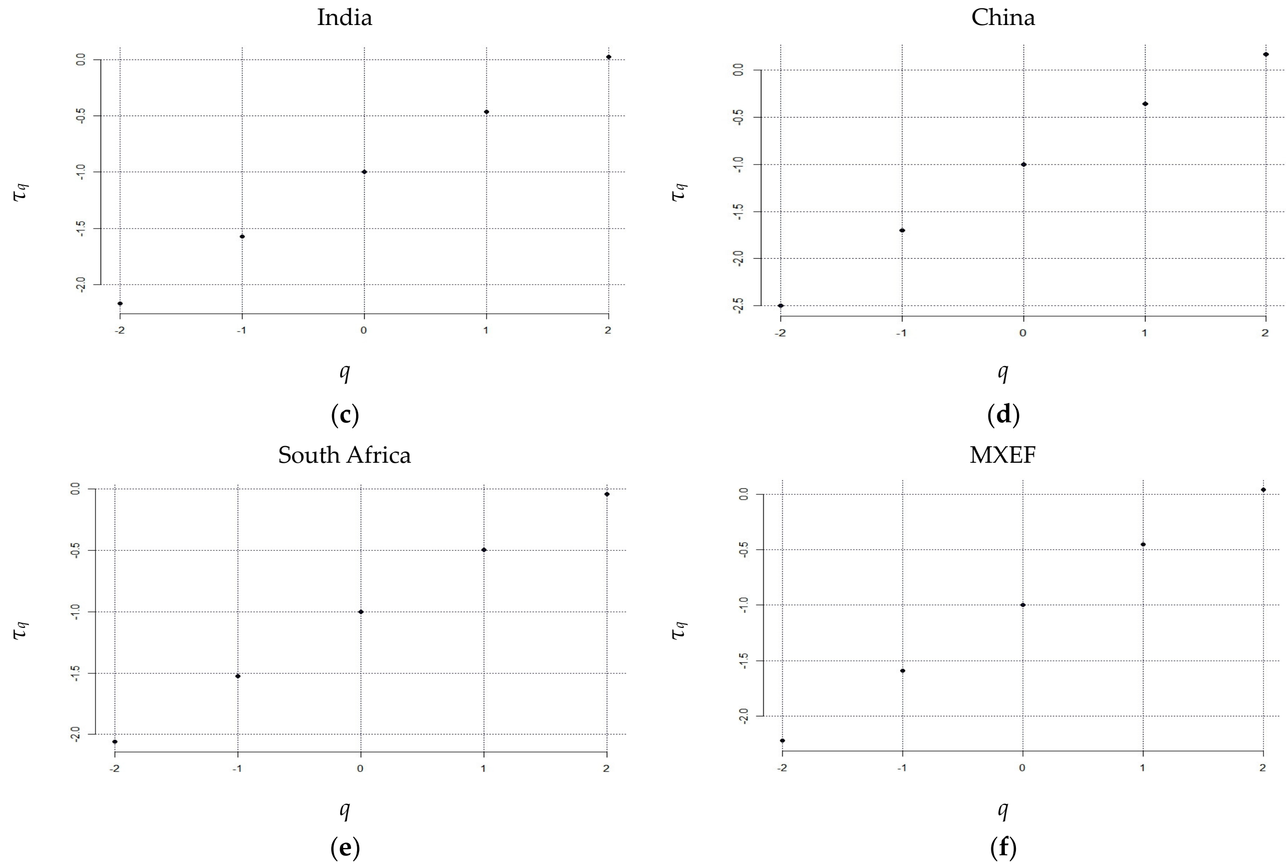


Figure 3. The Renyi exponents. The y-axis refers to τ_q while x-axis denotes q. Panels (**a**–**e**) indicate each of the BRICS index, while Panel (**f**) represents the MXEF.

3.2. Ranking BRICS Stock Market Efficiency

According to EMH, stock markets are considered efficient if they follow the random walk behaviour during all kinds of fluctuations, i.e., when all h_qs are equal to 0.5, the Brownian time series or classical random walk exists. Any deviation above or below 0.5 indicates inefficiency. The interpretation and ranking of the markets are completed on the basis of $h_{q=1}$ values using the conservative approach, as recommended by [34–36]. All $h_{q=1}$ values greater than 0.5 indicate the presence of multifractality in the return series. A higher value of $h_{q=1} - 0.5$ indicates a higher level of inefficiency in time series, and vice versa.

Table 4 presents the $h_{q=1} - 0.5$ values for the BRICS and benchmark MXEF indices and also ranks them in terms of their efficiency. The results indicate that South Africa is the most efficient stock market, while China is the least efficient. Nevertheless, MXEF is found to be the third least efficient index in the sample under study.

Table 4. Ranking of BRICS and MXEF in terms of stock market efficiency.

Rank	Country/Index	$h_{q=1} - 0.5$
1	China	0.1442
2	Russia	0.0511
3	MXEF	0.0467
4	India	0.0390
5	Brazil	0.0227
6	South Africa	0.0045

4. Subsample Analysis of the Impact of COVID-19 on Market Efficiency

4.1. Stock Returns during Pre- and Post-COVID Periods

To understand the impact of COVID-19 on the market efficiency of the BRICS and MXEF indices, the sample was divided into two periods. Data before 1 January 2020 represent the pre-COVID period, while the data after this date represent the post-COVID period. Table 5 presents the descriptive statistics for both periods.

Table 5. Descriptive statistics for the pre- and post-COVID returns.

	Brazil	**Russia**	**India**	**China**	**South Africa**	**MXEF**
			Panel A: Pre-COVID			
Mean	0.001126	0.000921	0.000551	0.000750	0.000472	0.000272
Median	0.001102	0.000893	0.000901	0.000657	0.000691	0.000754
Std. Dev.	0.021854	0.024940	0.014782	0.024657	0.011854	0.011101
Skewness	0.979245	0.897766	0.060064	12.096230	−0.300497	−0.359403
Kurtosis	19.355520	24.762950	10.588190	484.943500	8.574176	10.706560
Jarque–Bera	72,651	110,750	13,117	68,867,000	8019.20	19,537
Prob.	0.000	0.000	0.000	0.000	0.000	0.000
			Panel B: Post-COVID			
Mean	0.000519	0.000733	0.000821	0.000522	0.000542	0.000625
Median	0.001071	0.001766	0.001947	0.000776	0.001557	0.001292
Std. Dev.	0.024092	0.014377	0.017811	0.011989	0.016269	0.013305
Skewness	−1.069069	−0.667346	-1.300632	−0.736877	−0.924510	−0.933384
Kurtosis	15.162570	12.178310	15.381020	9.406056	10.784050	8.781479
Jarque–Bera	2363.70	1347.70	2480.90	651.74	1002.80	601.33
Prob.	0.000	0.000	0.000	0.000	0.000	0.000

4.2. Market Efficiency during the Pre- and Post-COVID Periods

Table 6 presents the pre- and post-COVID calculated slopes for the Hurst exponents. It is evident that the h_q values in both periods are changing gradually as q moves from -2 to 2. The decreasing function for h_q indicates that the presence of multifractality as is evident in all the time series during both the periods except the post-COVID periods in Russia, South Africa and MXEF. The varying values of h_q indicate the change in the market efficiency levels for all the time series over time. This is consistent with the adaptive market hypothesis, which states that market efficiency is not a static phenomenon and may vary over time. The adaptive market hypothesis harmonizes EMH using behavioural aspects of investors, incorporating the principles of competition, adaptation, natural selection and progressive evolution of financial interactions [42]. The results are also consistent with [43], indicating the presence of multifractality, and with [44], where less developed countries show more inefficiency, and the general increase in market inefficiencies because of the COVID-19 outbreak [45].

The positive correlation between the Hurst exponents h_q is evident, and it continues to exist in all the time series as we move from $q = -2$ to $q = 2$. This indicates the persistent behaviour of all the return series until $q = 2$. However, the post-COVID period in China and the pre-COVID periods in Brazil and South Africa attain a negative correlation or anti-persistent behaviour until we move to $q = 2$. Looking at the results for the post-COVID period, among the six indices, only China shows a Hurst exponent value that is below 0.5, indicating anti-persistent behaviour. This implies an improved market efficiency in the Chinese stock market during the COVID-19 period. The improved market efficiency in China can be attributed to the prompt and effective measures introduced by the Chinese government.

Table 6. Pre- and post-COVID generalized Hurst exponents for the BRICS and MXEF stock indices and their ranges over $q \in [-2, 2]$.

	−2	**−1**	**0**	**1**	**2**
			Panel A: Pre-COVID		
Brazil	0.5648	0.562	0.5542	0.5325	0.4938
Russia	0.6132	0.6132	0.6073	0.5727	0.5155
India	0.6281	0.6108	0.5897	0.5627	0.5314
China	0.7605	0.7094	0.6817	0.6468	0.5846
South Africa	0.551	0.5461	0.5374	0.5206	0.4953
MXEF	0.6245	0.6036	0.5818	0.5575	0.5288
			Panel B: Post-COVID		
Brazil	0.7457	0.7329	0.717	0.6828	0.6222
Russia	0.6007	0.6134	0.6345	0.6435	0.6189
India	0.6426	0.6159	0.6029	0.5961	0.5756
China	0.5781	0.5596	0.536	0.5057	0.4699
South Africa	0.5232	0.5251	0.5481	0.5789	0.5768
MXEF	0.5553	0.5556	0.5674	0.5828	0.5824

To contain the spread of COVID-19, China promptly imposed a full lockdown on 23 January 2020 that involved measures such as suspension of public gatherings, implementation of mass isolation of infected persons, the extension of public holidays, online schooling and home quarantines. While these measures substantially controlled the spread of COVID-19, they also triggered economic stagnancy, which severely impacted the financial markets [46]. To alleviate these situations, the stock market was opened on 2 February 2020 as a way to generate a positive signal regarding the economic conditions and to improve market liquidity [47]. In addition, the Chinese government introduced a range of fiscal, monetary, financial and trade policy packages to help economic recovery. These included fee waivers and tax deduction policies for enterprises and industries such as value-added tax exemptions for small businesses, cost reductions, subsidies [47] and a temporary waiver for social security contributions [46]. To ensure market liquidity and fulfil the needs of working capital, the People's Bank of China (PBC) also introduced several measures such as easing loan facilities and refinancing and providing re-discount policies [47]. Overall, the timely actions taken by the Chinese government resulted in a positive trend in the country's production and trade. This helped in building trust among the financial market participants and improved stock market efficiency during the pandemic.

As can be seen in Table 7, during the pre-COVID period, China is found to be the least efficient market, whereas, during the post-COVID period, China is seen as the most efficient stock market. In the case of Brazil, which was the second most efficient country during the pre-COVID period, it is evident that COVID-19 severely disrupted the market efficiency of Brazil, making it the most inefficient market during the post-COVID period.

Table 7. Pre- and post-COVID-19 $h_{q=1} - 0.5$-based ranking of market efficiency.

Pre-COVID Ranking			**Post-COVID Ranking**		
Rank	**Country/Index**	$h_{q=1} - 0.5$	**Rank**	**Country/Index**	$h_{q=1} - 0.5$
1	China	0.1468	1	Brazil	0.1828
2	Russia	0.0727	2	Russia	0.1435
3	India	0.0627	3	India	0.0961
4	MXEF	0.0575	4	MXEF	0.0828
5	Brazil	0.0325	5	South Africa	0.0789
6	South Africa	0.0206	6	China	0.0057

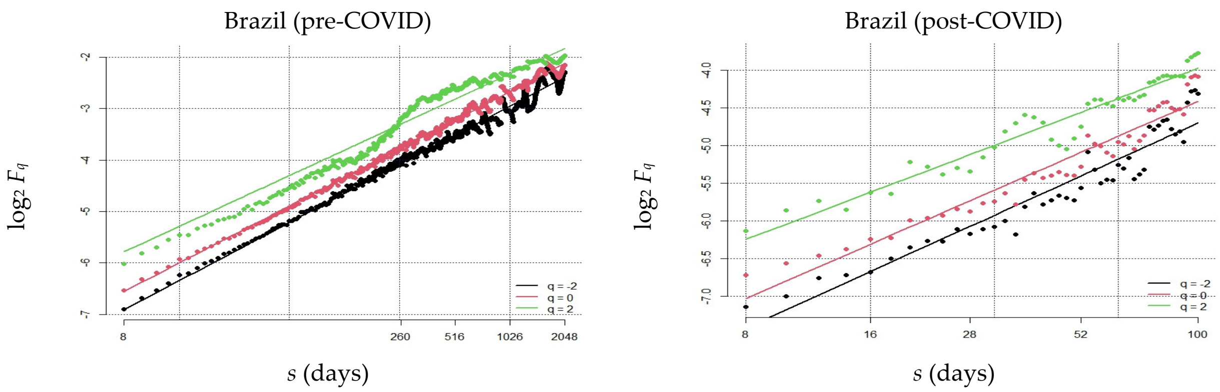
Table 8 confirms the notion that COVID-19 considerably impacted the market efficiency of BRICS and MXEF stock indices. All the non-zero values in the right column of Table 8 provide evidence that COVID-19 severely disrupted the market efficiency levels of these markets. Positive values indicate an increase in multifractality during the post-COVID periods, while negative values indicate a decrease in multifractality. Brazil shows greatest increase in multifractality, whereas MXEF shows a minimum increase in multifractality. These results indicating an increased inefficiency during the pandemic are consistent with the studies [7,45,48], which report an increased market inefficiency during COVID-19. Contrarily, the negative value for China shows the peculiar behaviour of China during the post-COVID period, indicating an improved market efficiency in response to COVID-19. This indicates an improvement in market efficiency during COVID-19. These findings are in line with [49], which reports an improvement in financial markets efficiency during COVID-19.

Table 8. Highest hit to lowest hit by COVID-19, calculated by subtracting post- and pre-COVID $h_{q=1} - 0.5$.

Rank	Country/Index	Post-COVID $h_{q=1} - 0.5$	Pre-COVID $h_{q=1} - 0.5$	Highly Hit to Lowest Hit
1	Brazil	0.1828	0.0325	0.1503
2	Russia	0.1435	0.0727	0.0708
3	South Africa	0.0789	0.0206	0.0583
4	India	0.0961	0.0627	0.0334
5	MXEF	0.0828	0.0575	0.0253
6	China	0.0057	0.1468	−0.1411

Note: The table is computed by deducting post-COVID $h_{q=1} - 0.5$ values and pre-COVID $h_{q=1} - 0.5$ values.

Figure 4 depicts the pre- and post-COVID scaling behaviour of the fluctuation functions for the indices under study. It is evident that the post-COVID fluctuations are more pronounced than the pre-COVID ones except for China. This implies an improved efficiency of the Chinese market during the post-COVID period. During the post-COVID period, the scale s = 8:2048 is not appropriate as the time series is less than 2048. Therefore, two estimations were calculated using two different scales, i.e., s = 8:100 and 8:256. The resulting GHEs and fluctuation functions are shown in Appendix C. It is evident from the fluctuation function graphs that the s = 8:100 scale shows a better fit. Hence, the scale 8:100 was used in our study for the post-COVID period.



(**a**) (**b**)

Figure 4. *Cont.*

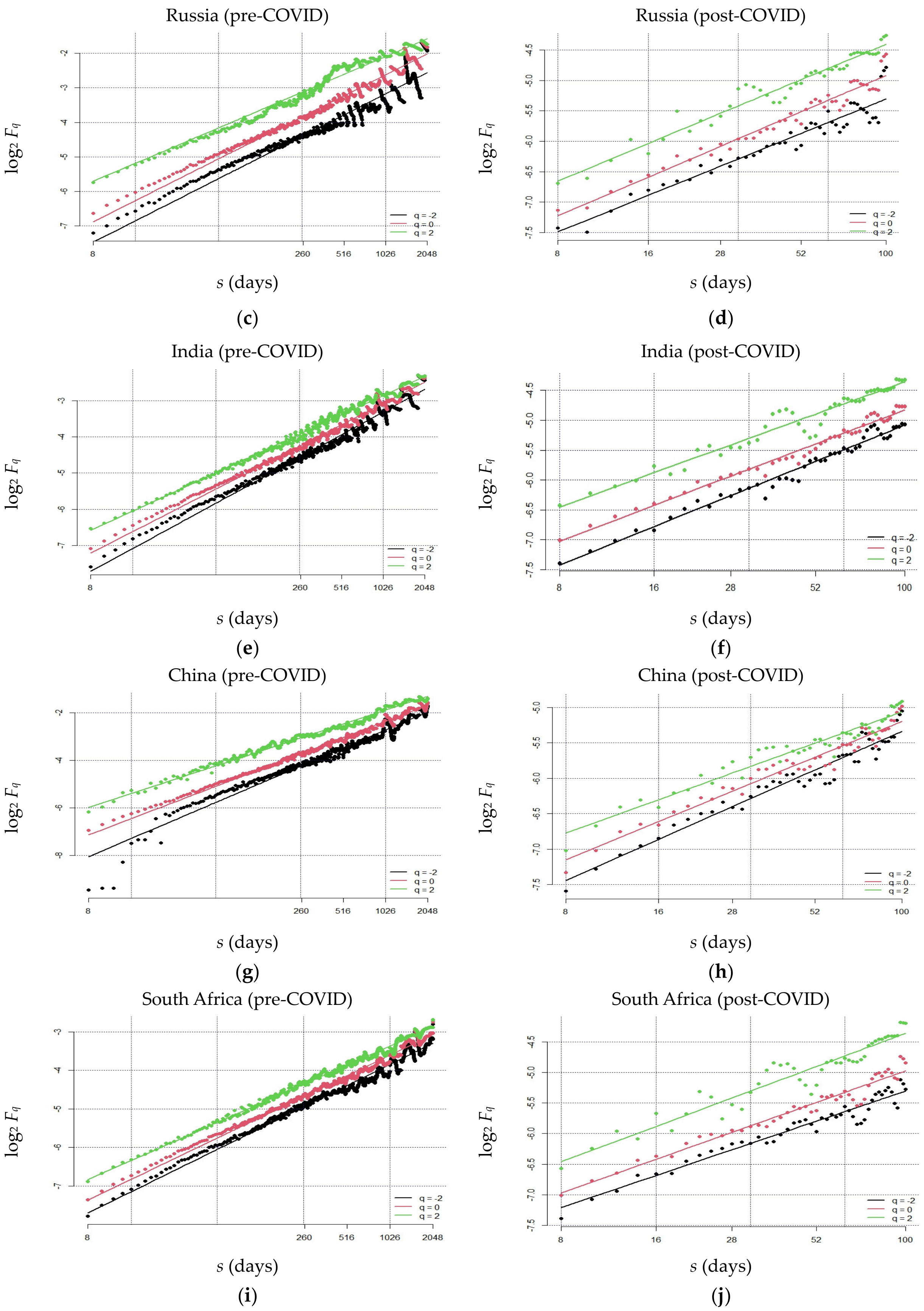
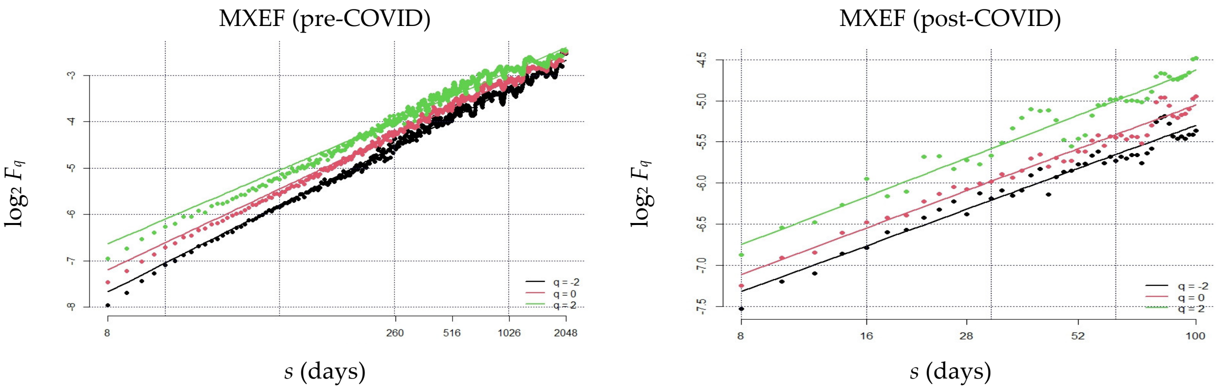


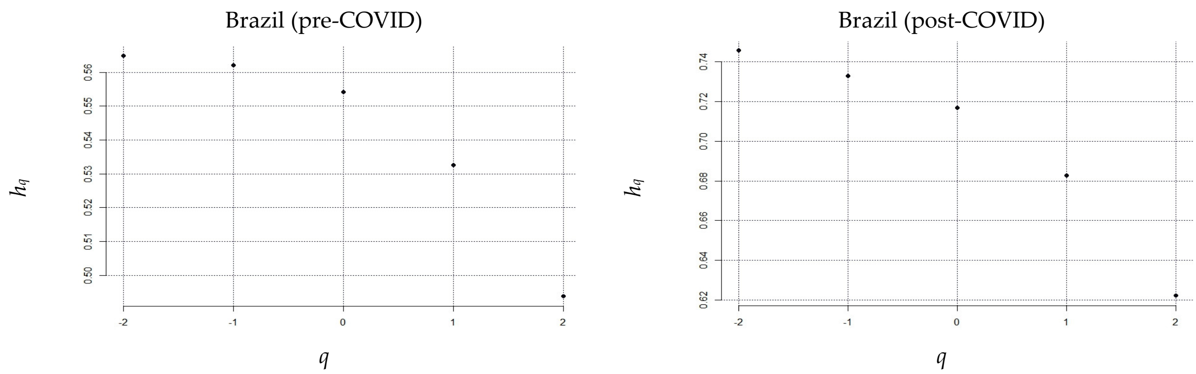
Figure 4. *Cont.*



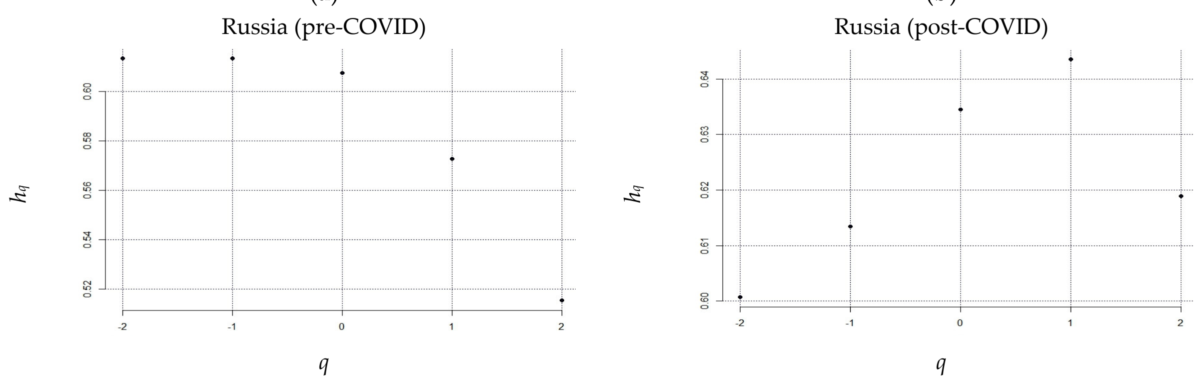
(**k**) (**l**)

Figure 4. Pre- and post-COVID scaling behaviour of the fluctuation function. The y-axis refers to $\log_2 F(q)$ while x-axis denotes *s* (days). Left column refers to pre-COVID, while right column indicates post-COVID: Panels (**a**–**j**) indicate the pairs for each of the BRICS index, while Panels (**k**,**l**) represent the pair for MXEF.

Figure 5 shows the pre- and post-COVID relationship between the generalized Hurst exponent h_q and q for the BRICS and MXEF indices. The declining graph is an indication that the patterns of multifractality exist in all the time series during both periods. However, the smoother Hurst exponent chart for China confirms a decline in multifractality during the post-COVID period.



(**a**) (**b**)



(**c**) (**d**)

Figure 5. *Cont.*

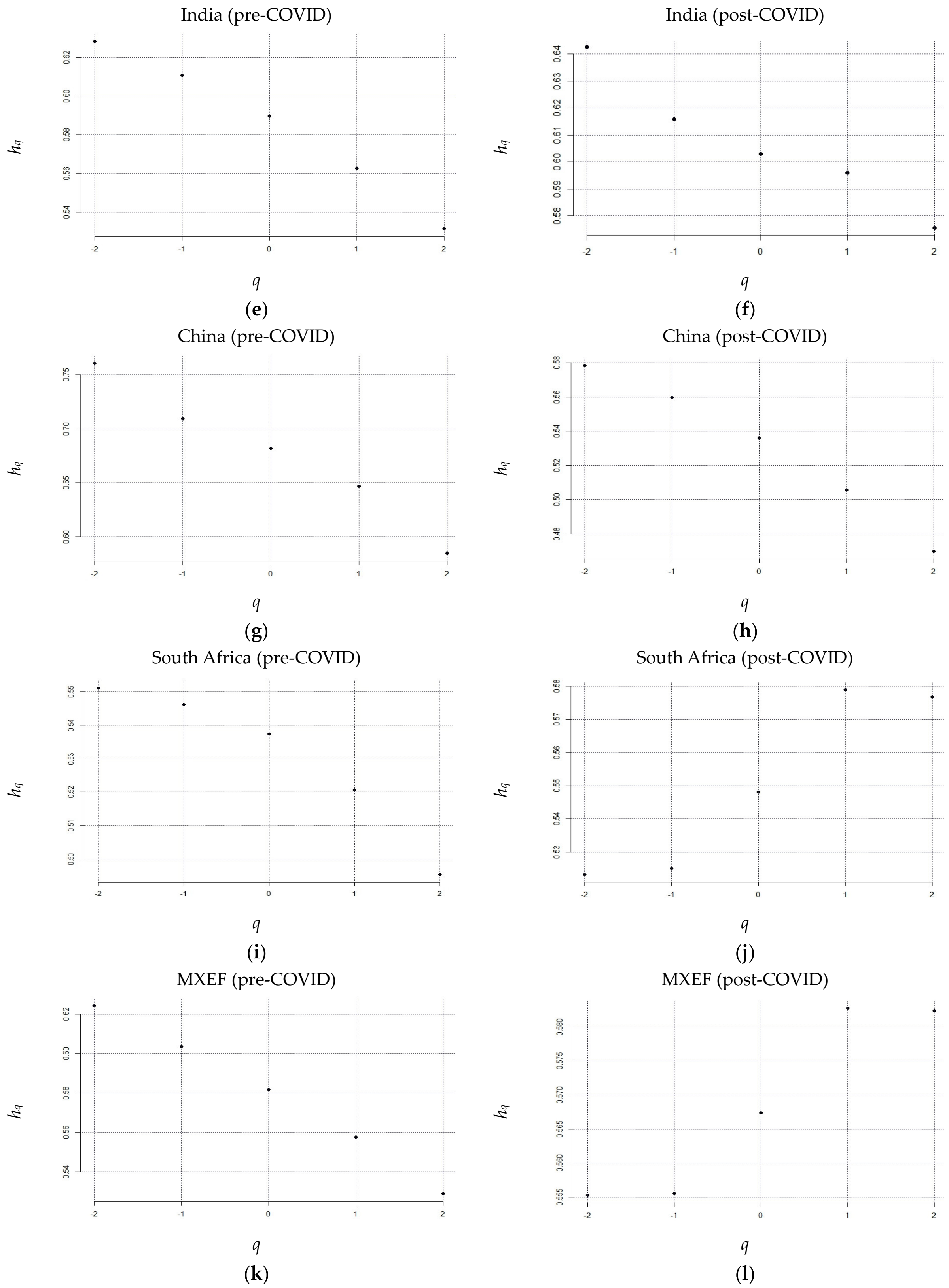


Figure 5. Relationship between the pre- and post-COVID generalized Hurst exponents h_q and q for BRICS and MXEF. The y-axis refers to h_q while x-axis denotes q. Left column refers to pre-COVID, while right column indicates post-COVID: Panels (**a**–**j**) indicate the pairs for each of the BRICS index, while Panels (**k**,**l**) represent the pair for MXEF.

Figure 6 depicts the pre- and post-COVID Renyi exponents. The exponential shape of multifractality indicates that the series are multifractal during both periods. However, less variation in the values for China implies that the efficiency of the Chinese market improved during the post-COVID period.

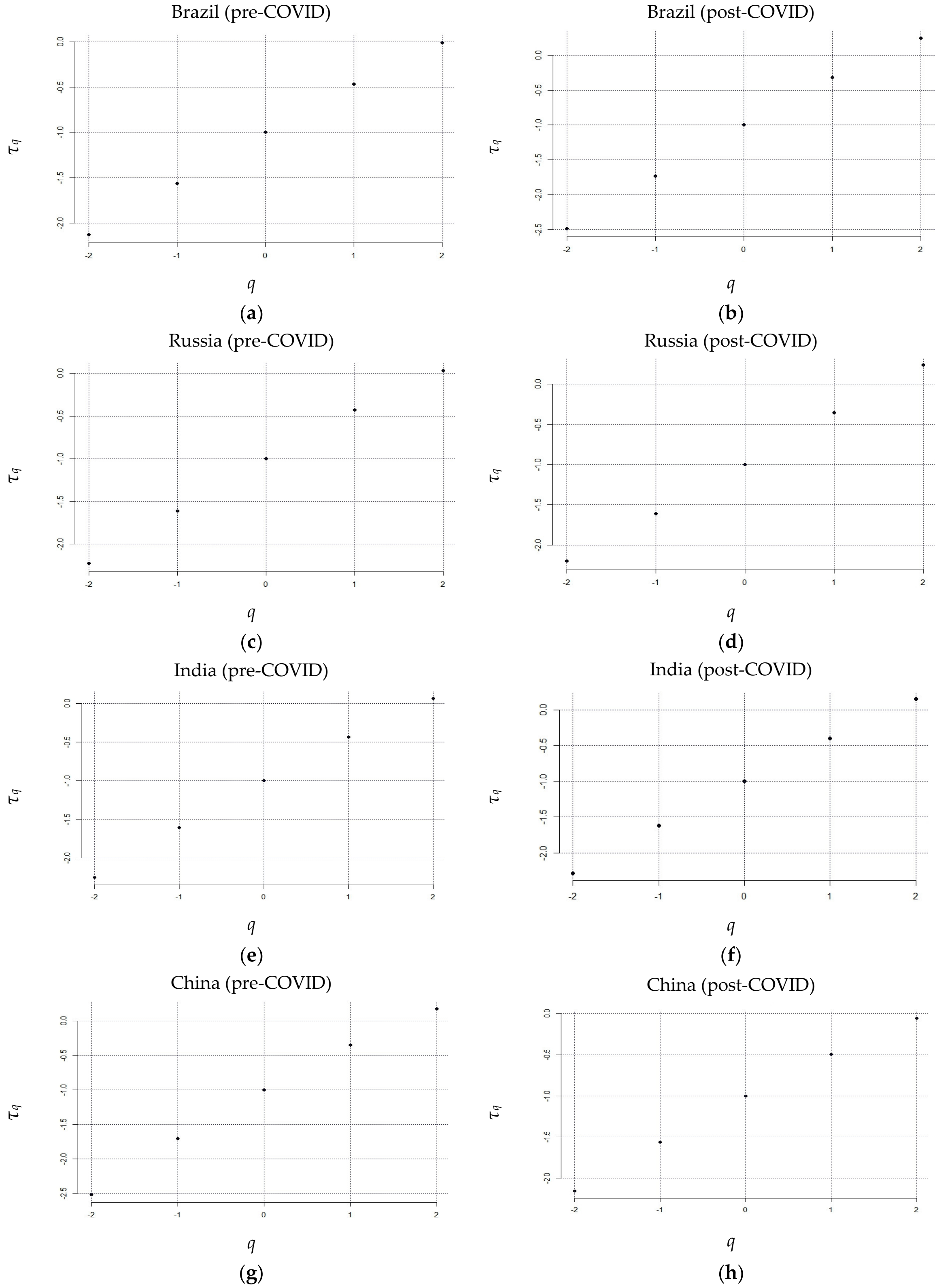


Figure 6. *Cont.*

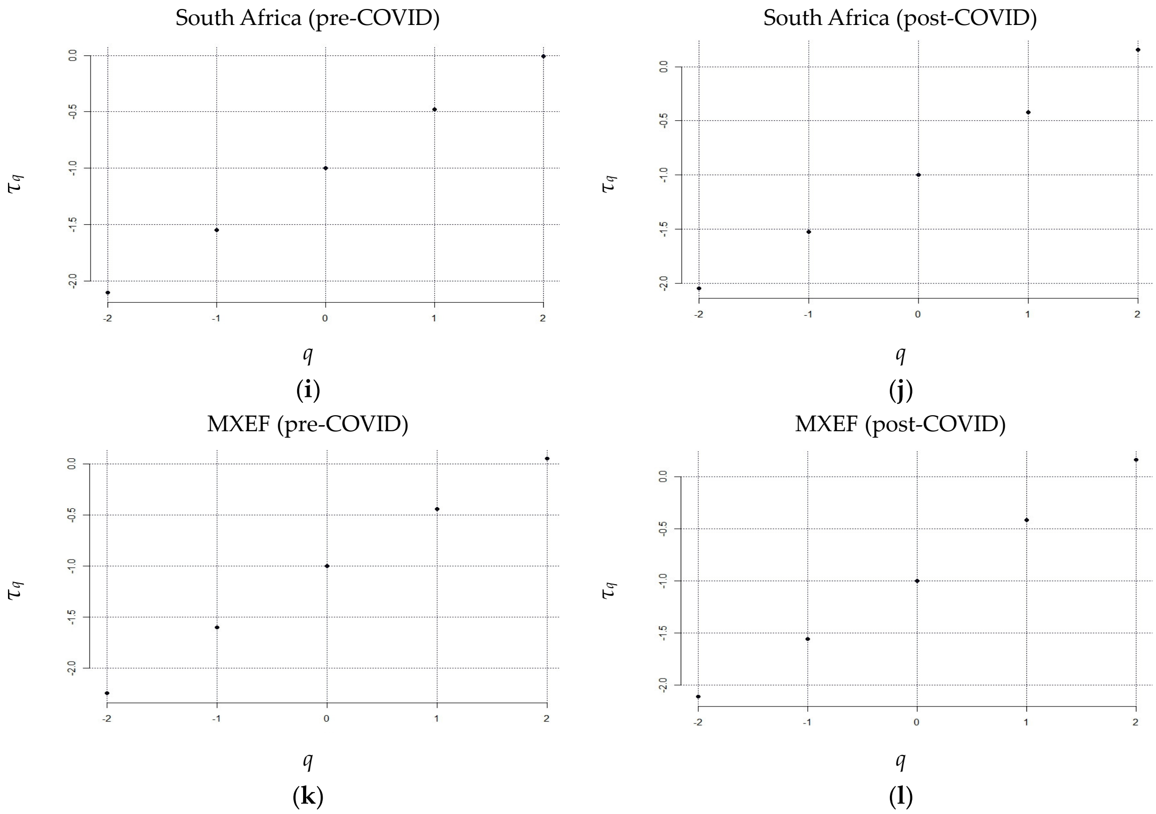


Figure 6. Pre- and post-COVID Renyi exponents. The y-axis refers to τ_q while x-axis denotes q. Left column refers to pre-COVID, while right column indicates post-COVID: Panels (**a**–**j**) show the pairs for each of the BRICS index, while Panels (**k**,**l**) indicate the pair for MXEF.

5. Conclusions and Implications

In this study, we used MF-DFA to examine and rank the market efficiency of the BRICS and MXEF indices. The Hurst exponents for the full-sample data indicate that the returns from the BRICS and MXEF indices exhibit long-range correlations, which imply that all six markets are not weak-form efficient. The efficiency ranking indicates that South Africa (China) is the most efficient (inefficient) stock market among all the indices under study.

In the subsample analysis, we explored the impact of the COVID-19 outbreak on the efficiency of the BRICS and MXEF indices. The findings for the pre-COVID period confirm the weak form inefficiency in all the indices. During the pre-COVID period, China is seen as the least efficient market, while in the post-COVID period, China is seen as the most efficient market. In contrast, Brazil turns out to be the most inefficient market during the post-COVID period. Based on the volatile and dynamic nature, it was an appropriate investment option to invest in the Chinese stock market to gain higher profits during the pre-COVID period and in Brazil during the post-COVID period.

Our empirical findings for the post-COVID period clearly show that COVID-19 adversely affected the efficiency of the markets under study. Overall, the results indicate an increase in market inefficiency during the post-COVID period except in China, which witnessed improved market efficiency during the post-COVID period. The considerable change in market efficiency ranking during the post-COVID period draws an important insight that the investment options as well as strategies should be adjusted according to the new scenario of the market efficiency rankings.

The empirical findings of our study regarding multifractality have important practical implications for both local and international market participants as they help the investors in decision-making by providing better insights into market dynamics, risk management, diversification and potential investment strategies [49]. The presence of multifractality indicates that different parts of the stock markets exhibit varying levels of complexity and scaling behaviour. It further explains the inherent non-linearity and heterogeneity in the market dynamics. Hence, investors can design their investment strategies accordingly. Multifractality also implies that risk is not uniformly distributed in stock markets across all time scales. Few time scales exhibit higher levels of extreme events than the others. Therefore, understanding the multifractal nature of the markets also helps the investors in managing risks.

Next, multifractality can help to identify the diversification potential of the investment portfolios because different stocks may exhibit different scaling behaviours [50]. Investors can reduce the impacts of extreme events by constructing portfolios that contain multifractal diversity. A multifractal analysis also highlights the diverse patterns in markets at different time scales, which can help to identify investment opportunities. Further, investors can make informed decisions by examining the multifractal properties of different markets to find stock market predictability. Prior studies show the existence of predictable price patterns, which can be exploited to generate abnormal profits (see, e.g., [51–54]). Hence, multifractality features, which can distinguish between market efficiency and lack thereof, can be incorporated into trading algorithms to enhance entry/exit points. Indeed, research using fractals as a market phase sensor for selecting indicators is basically non-existent, and this novel approach was only introduced recently in [55] for utilizing the appropriate momentum indicators (when the market is trending) or contrarian indicators (when the market is mean reverting). Future research can extend their approach by applying multifractal-based filters.

From a policymaking perspective, an efficient market with proper resource allocation contributes to the development of an economy by facilitating efficient channels of wealth distribution. However, inefficient markets resulting from a crisis will be detrimental to economic growth [54]. The identification of market efficiencies is important in finding the right actions. Therefore, our findings will help policymakers and regulators make decisions and use suitable approaches when re-designing fiscal or monetary policies. Countries such as Brazil, Russia, India and South Africa may consider the policies used by China to strengthen economic activities and market liquidity immediately following the COVID-19 crisis.

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Appendix A

Table A1. Market inefficiency calculation with different ranges of q (full period).

	***hq* (IBOV)**		
	$q = -10{:}10$	$q = -5{:}5$	$q = -2{:}2$
−10	0.6024		
−9	0.5969		
−8	0.5908		
−7	0.5843		
−6	0.5774		
−5	0.5706	0.5706	
−4	0.5641	0.5641	
−3	0.5586	0.5586	
−2	0.5545	0.5545	0.5545
−1	0.5507	0.5507	0.5507
0	0.5429	0.5429	0.5429
1	0.5227	0.5227	0.5227
2	0.486	0.486	0.486
3	0.4431	0.4431	
4	0.4059	0.4059	
5	0.3773	0.3773	
6	0.3557		
7	0.3392		
8	0.3262		
9	0.3159		
10	0.3073		

Note: Inefficiency at $q = 1$, using ($q = -10{:}10$). hq (1) = 0.5227 − 0.5 = 0.0227. Inefficiency at $q = 1$, using ($q = -5{:}5$). hq (1) = 0.5227 − 0.5 = 0.0227. Inefficiency at $q = 1$, using ($q = -2{:}2$). hq (1) = 0.5227 − 0.5 = 0.0227. Hence, in our analysis, there is no difference in market inefficiency for IBOV when we use different ranges of q.

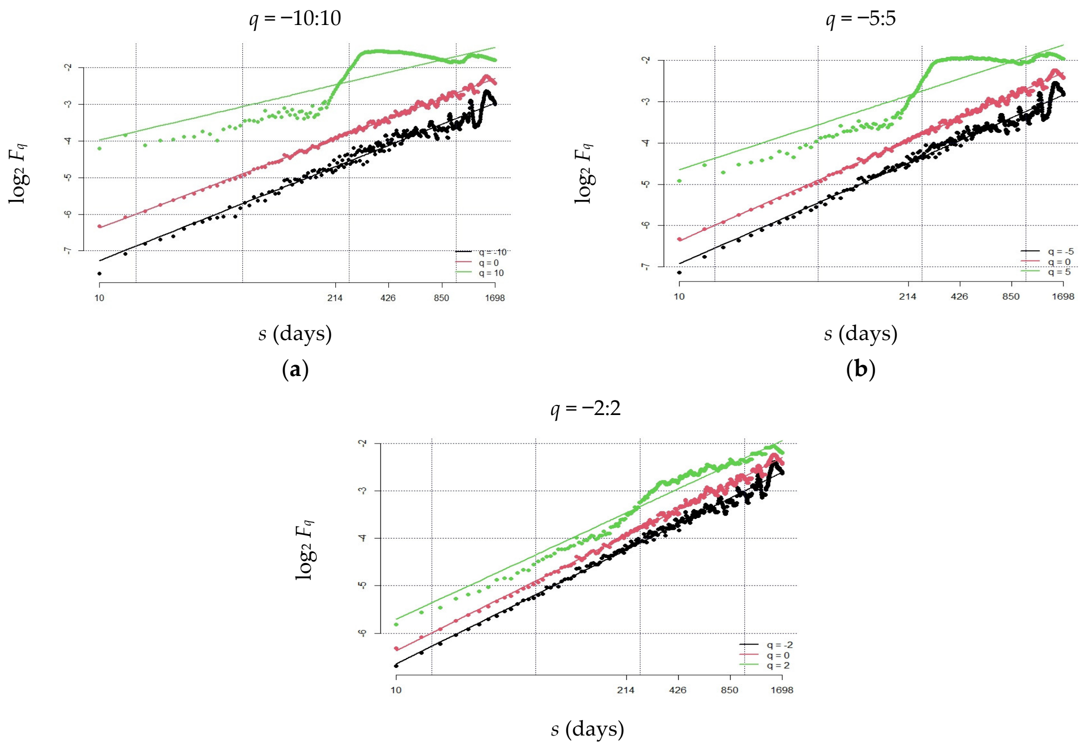

Figure A1. Market inefficiency calculation with different ranges of q (full period) for IBOV. The y-axis refers to $\log_2 F(q)$ while x-axis denotes s (days): (**a**) $q = -10$ to 10; (**b**) $q = -5$ to 5; (**c**) $q = -2$ to 2.

Appendix B

Table A2. Market inefficiency calculation with different scales (s) (full period).

	hq (IBOV)		
	s = 8:512	s = 8:1024	s = 8:2048
−10	0.6324	0.568	0.6024
−9	0.6253	0.5619	0.5969
−8	0.6174	0.5554	0.5908
−7	0.6086	0.5485	0.5843
−6	0.5991	0.5417	0.5774
−5	0.5890	0.5354	0.5706
−4	0.5785	0.5306	0.5641
−3	0.5682	0.5286	0.5586
−2	0.5592	0.5311	0.5545
−1	0.5540	0.5393	0.5507
0	0.5587	0.5519	0.5429
1	0.5832	0.5622	0.5227
2	0.6267	0.5617	0.4860
3	0.6625	0.5496	0.4431
4	0.6773	0.5326	0.4059
5	0.6789	0.5164	0.3773
6	0.6754	0.5029	0.3557
7	0.6703	0.4918	0.3392
8	0.6650	0.4827	0.3262
9	0.6599	0.4751	0.3159
10	0.6553	0.4686	0.3073

Note: Inefficiency at $q = 1$, using (s = 8:512). *hq* (1) = 0.5832 − 0.5 = 0.0832. Inefficiency using at $q = 1$, (s = 8:1024). *hq* (1) = 0.5622 − 0.5 = 0.0622. Inefficiency at $q = 1$, using (s = 8:2048). *hq* (1) = 0.5227 − 0.5 = 0.0227. A shorter s results in a high value for IBOV market inefficiency.

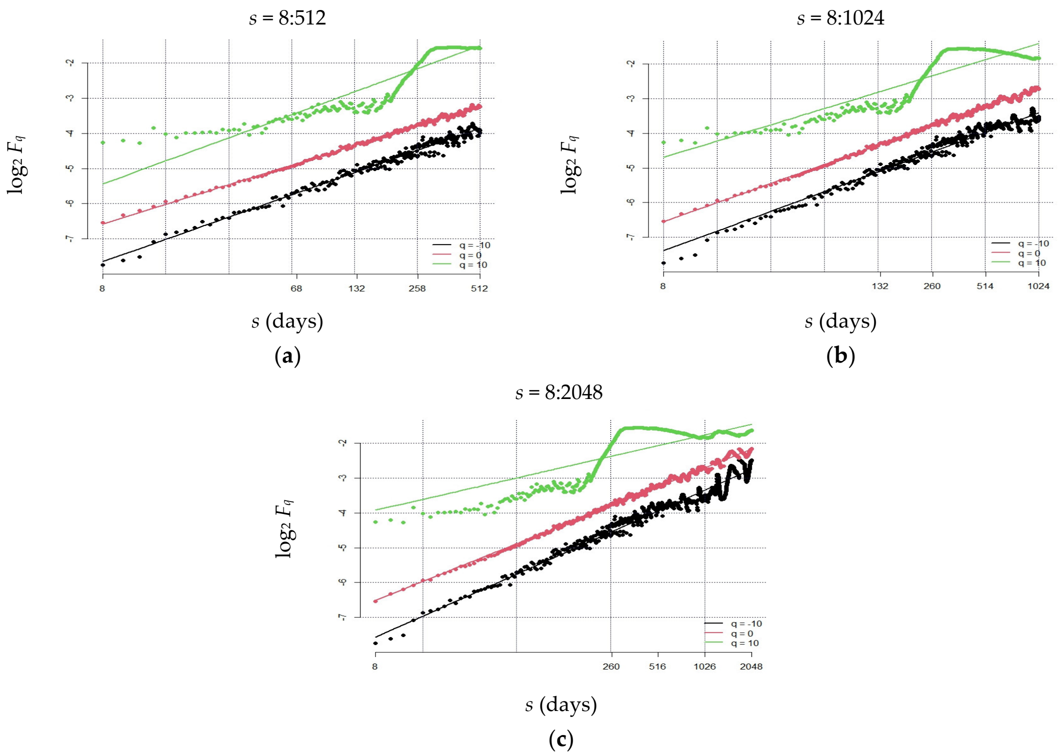

Figure A2. Market inefficiency calculation with different scales (s) (full period) for IBOV. The y-axis refers to $\log_2 F(q)$ while x-axis denotes s (days): (**a**) s = 8 to 512 days; (**b**) s = 8 to 1024 days; (**c**) s = 8 to 2048 days.

Appendix C

Table A3. Market inefficiency with different ranges of scale (s) (post-COVID).

	***hq* (IBOV)**	
	s = 8:100	**s = 8:256**
−2	0.7457	0.9744
−1	0.7329	0.9441
0	0.7170	0.8996
1	0.6828	0.8263
2	0.6222	0.7298

Note: Inefficiency at q = 1, using (s = 8:100). *hq* (1) = 0.6828 − 0.5 = 0.1828. Inefficiency at q = 1, using (s = 8:256). *hq* (1) = 0.8263 − 0.5 = 0.3263.

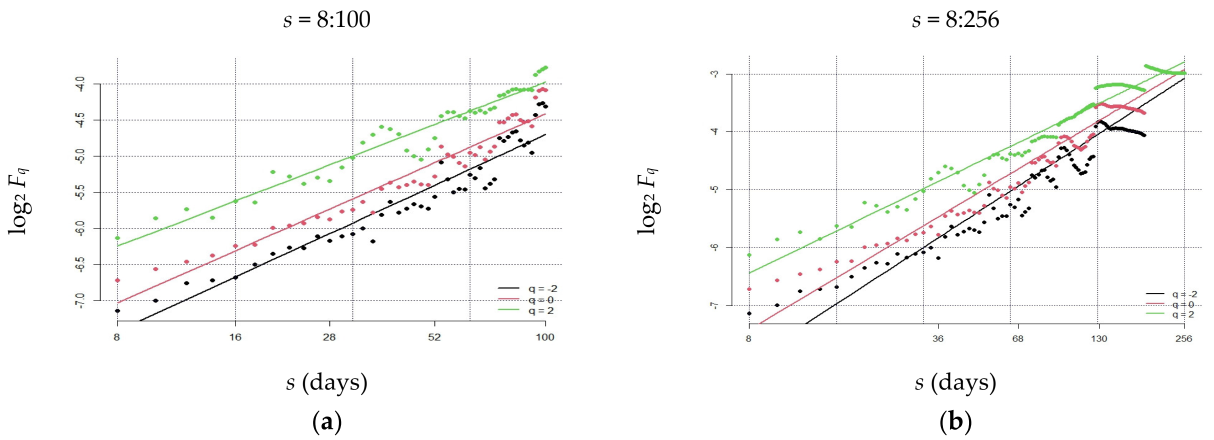

Figure A3. Market inefficiency with different ranges of scale (s) (post-COVID) for IBOV. The y-axis refers to $\log_2 F(q)$ while x-axis denotes s (days): (**a**) s = 8 to 100 days; (**b**) s = 8 to 256 days.

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