International Economics 177 (2024) 100463

Contents lists available at ScienceDirect

International Economics

journal homepage: www.elsevier.com/locate/inteco

# A multifractal detrended fluctuation analysis of Islamic and conventional financial markets efficiency during the COVID-19 pandemic

Syed Ali Raza [a], Nida Shah [c], Muhammed Tahir Suleman [b,*]

[a] Department of Business Administration, IQRA University Karachi, Pakistan and Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon
[b] Department of Accountancy and Finance, University of Otago, Dunedin, New Zealand
[c] Department of Business Administration Sirsyed University of Engineering and Technology Karachi, Pakistan

A R T I C L E I N F O

*JEL classification:*
G1 General Financial Markets
G11 Portfolio Choice
Investment Decisions
G14 Information and Market Efficiency
Event Studies
Insider Trading

*Keywords:*
DJIM islamic markets' efficiency
*Covid-19 pandemic*
*MF-DFA technique*

A B S T R A C T

This paper examines the efficiency of DJIM conventional and Islamic sectoral stock markets before and during the Covid-19 period. The study uses both sectoral stock markets' daily data from January 1, 2010, to August 1, 2022, and relies on the multifractal detrended fluctuation analysis (MF-DFA). Firstly, we find that the conventional and Islamic sectoral stock markets are multifractal in the short and long run. Secondly, conventional and Islamic sectoral stock markets are characterized by long-term memory features in small fluctuations. Thirdly, in terms of efficiency before the Covid-19 period, in the Islamic sectoral market, the healthcare sector is the most efficient in the short run, and the financial sector is the most efficient in the long run. During the Covid-19 period, in the conventional sectoral market, the financial sector was the most efficient in the short run, and the utility sector was the most efficient in the long run.

## 1. Introduction

Covid-19 consider one of the first deadly global pandemics after the Spanish flu in 1918 (Papadamou et al., 2020). This outbreak shows the example of world fragility and the people's vulnerability as a society to unique risks (Corbet et al., 2020). It is foremost a human tragedy that affects thousands of people worldwide. Due to its infectious nature, many countries observed strict lockdown. They restricted their economic agents from mobilizing from one country to another and even within the country, cancelling their flights and restricting labor mobility (Singh and Neog, 2020; Dunford et al., 2020). All these measures impact the global economy, and unfortunately, the global health crisis shifted into a global economic crisis (Singh and Neog, 2020).

Covid-19 greatly impacts real economic activities, but its actual impact still needs to be known (Ashraf, 2020). On one end, the government is taking precautionary measures to overcome the cases. Conversely, government finance ministries are announcing stimulus packages and supporting economic damage (Ashraf, 2020). According to Goodell (2020), the pandemic is causing unprecedented global destructive economic damage and has a wide-ranging impact on financial sectors such as banking, insurance, and stock markets. It is of immense importance to scrutinize financial markets' performance, especially the stock markets, as Covid-19 causes the most visible effect on this market (Ozili and Arun 2020). According to S&P Dow Jones Indices, from 23 to 28th February, the Global

* Corresponding author.
*E-mail addresses:* syed_aliraza@hotmail.com (S.A. Raza), nidashah_18@hotmail.com (N. Shah), tahir.suleman@otago.ac.nz (M.T. Suleman).

https://doi.org/10.1016/j.inteco.2023.100463
Received 11 March 2021; Received in revised form 16 August 2023; Accepted 10 November 2023
Available online 15 November 2023

stock markets lost $6 trillion. Between February 20 and March 19, the Nikkei index fell by from 23,479 to 16,552 (i.e., 29%), the FTSE 250 index fell from 21,866 to 12,830 (i.e., 41.3%) and the S&P 500 index fell from 3373 to 2409 (i.e., 28%). Moreover, in March, the stock market's subsequent fall was observed due to investors' flight to safety during this pandemic (Ozili and Arun 2020). It brings unprecedented volatility to the stock market, and the prices change with the news of Covid-19.

Numerous studies have analyzed the impact of Covid-19 and other financial crises on overall financial markets (Zhang et al. (2020); stock markets (Ashraf, 2020), precious metals (Yuandong et al., 2022); cryptocurrencies (Raza et al., 2022) and share prices (Al-Awadhi et al. (2020) but the Islamic stock markets ignores (Mensi et al., 2017). The literature on the Islamic stock markets is very scarce and at its early stage. Few studies have examined the Islamic stock market association with other commodities or assets (Hammoudeh et al., 2016; Narayan et al., 2019). Some studies examine the efficiency of Islamic stock markets and reported mixed results (Jawadi et al., 2015; Kok et al., 2009). Rizvi et al. (2014) reported that the Islamic stock market is less efficient in crisis times. Mensi et al. (2017) used ten sectoral Islamic stock indices' data and reported that the market efficiency changes over time. They reported high efficiency in the long run and weak efficiency in the short run. They further noted that the markets became less efficient after the global financial crisis. Mensi et al. (2018) examined the stock market efficiency of five Gulf Cooperation Council and reported that the efficiency varies with timeframes and is sensitive to time horizons. They suggested that the Islamic market is more efficient in the long run than in the short run. Al-Khazali and Mirzaei (2017) also reported that the Dow Jones Islamic indices have become more efficient. Haddad et al. (2020) also used the data of seven DJIM (Dow Jones Islamic stock markets). They reported that Asia-Pacific, Canada, and Japan markets are most subtle to domestic shocks. In contrast, the GCC, Europe, USA, and the UK markets are stable to foreign and domestic shocks. Moreover, all seven markets are weakly linked to the movements of global risk factors.

The above studies show the absence of unanimity regarding the Islamic sectoral stock market efficiency. This discrepancy motivates us to analyze the Islamic stock market efficiency from a new perspective. Against this backdrop, this study investigates the efficiency of the Islamic sectoral stock market in the COVID-19 pandemic as it brings considerable uncertainty to the global economy. This uncertainty highlights the fragility and the risk linked with the standard financial and economic structures that govern the conventional monetary and financial systems. In this scenario, the Islamic market is considered a good alternative for investors because of its base on Shariah Regulation (Jawadi et al., 2015). They differ from the traditional markets in terms of risk aversion, market efficiency, information transmission, and linkages with other financial markets (Lin and Su, 2020). To the best of our knowledge, no study examines the DJIM Islamic stock market efficacy efficiency using the MF-DFA technique in the Covid-19 pandemic. Furthermore, we also compare the Islamic stock market efficiency with conventional sectoral stock market efficiency.

MF-DFA technique is a mixture of two methods (i) multifractal Methods (MF) and (ii) detrended fluctuation analysis (DFA) (Mensi et al., 2017). MF method considers a monofractal approach given by Mandelbrot, Fisher, and Calvet (1997). It analyses the price dynamics of housing markets. This technique has been used in some studies and gives spurious results (Di Matteo et al., 2003; Oświe et al., 2005). In contrast, DFA detects a mono-fractal scaling method that determines long-term correlations in nonstationary and noisy time series (Chen et al., 2002). According to Horvatic et al. (2011), the MF-DFA technique is an extension of the DFA technique proposed by Kantelhardt et al. (2002). This technique explores the multifractal spectrum of a stochastic process for a financial time series. It deducts the monofractal and multifractal behavior of the financial data. It allows determining the degree of time-varying efficiency, long-run correlations of volatility, and the financial series's predictability. Moreover, this technique offers a reliable multifractal characterization of multifractal nonstationary financial time series. These features of MF-DFA make this technique appealing compared to others. This technique is widely used in the financial literature to analyze financial markets' fractal nature and behavior under a new dimension (Rizvi et al., 2014; Arshad et al., 2016; Ali et al., 2018; Tiwari et al., 2019). In this study, this technique gives information related to the random walk behavior, range memory, degree of persistence, and efficiency of Islamic stock markets.

This study contributes to the existing studies in five ways. Firstly, this is the first study examining the efficiency of DJIM conventional and Islamic sectoral stock markets in the Covid-19 period. Secondly, this study also explores the DJIM conventional and Islamic sectoral stock markets' by dividing the sample into two periods, i.e., before and during the Covid-19 period. Furthermore, the study strives to investigate if the Covid-19 pandemic determines the change in the degree of market efficiency or not. Thirdly, this study contributes to the existing literature that analyzes the Islamic market performance during various crises or disasters (Kenourgios et al., 2016; Mensi et al., 2017). Kenourgios et al. (2016) studied the impact of the global and Eurozone sovereign debt crisis on Islamic equity and bond markets. Mensi et al. (2017) studied the global financial crisis's effect on the Islamic stock market's efficiency. This study complements these by examining the Islamic market efficiency in the Covid-19 period. Fourth, this study will contribute to the recent studies which examine the effect of Covid-19 on stock markets (Alfaro et al., 2020; Zhang et al., 2020; Al-Awadhi et al., 2020). Lastly, this study examines this association using the advanced economic technique MF-DFA.

The rest of the paper is organized as follows. Section 2 discusses the methodology; Section 3 explains the data used in the empirical analysis. Section 4 presents a discussion of the empirical results. Lastly, Section 5 concludes the paper.

## 2. Methodology

In this study, we used the MF-DFA technique that Kantelhardt et al. (2002) developed. It is considered a powerful tool for analyzing multifractality in nonstationary time series. The existence of multifractality in the financial series reflects market inefficiency. Because multifractal properties are caused by the fat-tail distribution or long-range correlation properties, they are considered a signal of market inefficiency (Zhou, 2009). This technique gives information on the level of persistence, long-range dependence, and efficiency in financial data. This method is more flexible than other approaches to determine the long-range correlation in nonstationary time series and avoid misjudgment of correlation. This technique allows measuring the random walk behavior, persistence, and anti-persistence in financial data. The MF-DFA technique is widely used to explore the complexity of financial markets such as stock markets (Onali and Goddard, 2009; Rizvi et al., 2014), exchange markets (Wang et al., 2011; Norouzzadeh and Rahmani, 2006), international capital flows (Ning et al., 2017), crude oil markets (Cao et al., 2013), etc.

According to Kantelhardt et al. (2002), the MF-DFA technique is performed in five steps:

Let's assume the time series be $\{\chi_t t = 1, \ldots, N\}$.

In the first step, the profile is determined:

$$y_k = \sum_{t=1}^{k} [x_i - \bar{x}], K = 1, \ldots, N, \tag{1}$$

Where $\bar{x}$ represents the average over the whole time series.

In the second step, the profile $y_i$ is divided into $N_s \equiv f\left(\frac{N}{S}\right)$ which is non-overlapping windows (segments) of equal length $s$.

In the third step, the local trend for each of the $2N_S$ segments are computed by using the least-squares fit of the series, and the variance is determined by:

$$\mathrm{F}^2(\mathrm{s}, \mathrm{v}) = \frac{1}{\mathrm{s}} \sum_{\mathrm{i}=1}^{\mathrm{s}} \{\mathrm{y}[\mathrm{v}\text{-}1)\mathrm{s} + \mathrm{i}]\text{-}\mathrm{y}_\mathrm{v}(\mathrm{i})\}^2 \tag{2}$$

For $v = 1, 2, \ldots, N_s$ and

$$\mathrm{F}^2(\mathrm{s}, \mathrm{v}) = \frac{1}{\mathrm{s}} \sum_{\mathrm{i}=1}^{\mathrm{s}} \{\mathrm{y}[\mathrm{N}\text{-}(\mathrm{v}\text{-}\mathrm{N}_\mathrm{s})\mathrm{s} + \mathrm{i}]\text{-}\mathrm{y}_\mathrm{v}(\mathrm{i})\}^2 \tag{3}$$

For $v = N_s + 1, \ldots, 2N_s$.

In the fourth step, the $q^{th}$ order fluctuation function $F_q(s)$ is calculated by taking an average of all the other subsets (segments):

$$F_q(s) = \left\{\frac{1}{2N_s} \sum_{v=1}^{2N_s} \left\{F^2(s, v)\right]^{q/2}\right\}^{1/q} \tag{4}$$

In fifth, the scaling behaviour of fluctuation functions is determined by analyzing the log-log plots $F_q(s)$ versus s for each value of $q$.

If, in the long term, the series $x_i$ are correlated, then $F_q(s)$ increases for a large value of $s$, based on the power law:

$$F_q(s) \sim s^{h(q)} \tag{5}$$

In General, the $h(q)$ exponent depends on $q$. The series is considered multifractal if $h(q)$ depends on $q$ and considered monofractal if $h(q)$ does not depend on $q$. It implies that the scaling behaviour of large variations ($q > 0$) is different from the small variations ($q < 0$) (Mensi et al., 2017). For stationary series, $h(2)$ is similar to the well-known Hurst exponent ($H$), and therefore, $h(q)$ is explained as a generalized Hurst exponent. The exponent analyzes the correlation in the time series $h(2)$. If the value of $h(2) = 0.5$ means that the series is not correlated and follows a random walk behaviour. The series implies long-term persistence if $0.5 < h(2) < 1$ and implies

**Table 1**
Descriptive statistics before the COVID-19 period.

| | Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | J-B | ADF test |
|---|---|---|---|---|---|---|---|---|
| **Sectoral Stock (Islamic)** | | | | | | | | |
| Basic Materials | 0.000034 | 0.024424 | −0.034479 | 0.004543 | −0.344406 | 7.244290 | 2008.308*** | −21.369*** |
| Consumer Services | 0.000197 | 0.016984 | −0.023327 | 0.003358 | −0.514183 | 6.465465 | 1419.401*** | −21.676*** |
| Consumer Goods | 0.000163 | 0.016948 | −0.019419 | 0.002964 | −0.554869 | 7.084245 | 1945.754*** | −22.734*** |
| Energy | −0.000004 | 0.021419 | −0.031094 | 0.005137 | −0.313141 | 5.760729 | 870.505*** | −20.365*** |
| Financials | 0.000203 | 0.019439 | −0.024989 | 0.003653 | −0.357312 | 6.811105 | 1633.199*** | −25.126*** |
| Health Care | 0.000193 | 0.013979 | −0.018129 | 0.003305 | −0.452221 | 5.604582 | 825.752*** | −20.353*** |
| Industrials | 0.000177 | 0.019593 | −0.023602 | 0.003776 | −0.484396 | 7.002905 | 1842.477*** | −22.660*** |
| Technology | 0.000222 | 0.020369 | −0.023490 | 0.004342 | −0.421307 | 5.731626 | 887.659*** | −21.568*** |
| Telecommunications | 0.000059 | 0.014918 | −0.021446 | 0.003061 | −0.371523 | 6.186132 | 1162.674*** | −20.521*** |
| Utilities | 0.000036 | 0.016060 | −0.024244 | 0.003256 | −0.399920 | 6.656821 | 1522.063*** | −20.272*** |
| **Sectoral Stock (Conventional)** | | | | | | | | |
| Basic Materials | 0.000084 | 0.029008 | −0.037317 | 0.005545 | −0.348701 | 6.868125 | 1678.121*** | −22.573*** |
| Consumer Services | 0.000236 | 0.024276 | −0.028884 | 0.004074 | −0.523194 | 7.138108 | 1979.024*** | −21.987*** |
| Consumer Goods | 0.000147 | 0.016495 | −0.022268 | 0.003414 | −0.494205 | 6.265009 | 1264.095*** | −22.047*** |
| Energy | 0.000002 | 0.027091 | −0.038083 | 0.005851 | −0.284166 | 5.740734 | 851.036*** | −19.895*** |
| Financials | 0.000161 | 0.033986 | −0.044443 | 0.004945 | −0.434859 | 9.772369 | 5064.249*** | −20.150*** |
| Health Care | 0.000206 | 0.019650 | −0.024567 | 0.004057 | −0.443693 | 5.911369 | 1006.250*** | −20.548*** |
| Industrials | 0.000168 | 0.021126 | −0.024781 | 0.003785 | −0.480624 | 7.282455 | 2092.488*** | −22.560*** |
| Technology | 0.000232 | 0.026520 | −0.025969 | 0.004900 | −0.370260 | 5.874138 | 956.887*** | −21.482*** |
| Telecommunications | 0.000081 | 0.020458 | −0.025854 | 0.004094 | −0.385929 | 5.383225 | 681.678*** | −20.290*** |
| Utilities | 0.000132 | 0.017265 | −0.025556 | 0.003788 | −0.481933 | 5.599385 | 834.874*** | −21.587*** |

Note: J-B = Jarque-Bera test of Normality, and ADF = augmented Dickey and Fuller (1979) test of stationary.*** denotes the rejection of the null hypothesis at 1%.

anti-persistence if $0 < h(2) < 0.5$.

## 3. Data and descriptive statistics

This study analyses the DOW Jones conventional and Islamic sectoral stock market performance before the Covid-19 and during the Covid-19 period. We used daily data from January 1, 2010 to August 1, 2022, further sub-divided into two spans. The first dataset comprised January 1, 2010 to December 31, 2019, which reflects the before Covid-19 period, and the second dataset comprised January 1, 2020 to August 1, 2022, which shows during the Covid-19 period. We used ten Islamic and conventional sectoral indices for empirical analysis, i.e., utilities, telecommunications, technology, industrials, health care, financials, energy, consumer goods, consumer services, and basic material.

The descriptive statistics are depicted in Table 1 and Table 2. Table 1 reflects the before Covid-19 period, and Table 2 shows the during the Covid-19 period. As seen from the tables, the average values of all the conventional and Islamic sectoral stocks are positive except for energy in the Islamic sectoral market before the Covid-19 period and telecommunications in the conventional sectoral market. Moreover, in both tables, the value of Skewness is negative for both sectoral stock markets meaning that the data skewed left and is not perfectly symmetrical. On the other hand, the value of Kurtosis is above 3 for all the series indicating a fat-tailed distribution and sharp peaks in both sectoral markets. The Jarque–Bera test also rejects the null hypothesis of the normal distribution for both sectoral markets. Moreover, the unit root test also indicates that the variable series is stationary.

## 4. Empirical analysis

We presented the results from the MF-DFA technique with the help of the figures. The scaling behavior of the returns is shown in figures (1-4). The log-log plot between the length scale and the order of the fluctuation function is used to analyze the fractality of the sectoral prices. The graphs show that it is crucial to determine a linear behavior from the scaling range as it ends on both upper and lower cutoffs. Moreover, the slope of the plot also changes with crossover times scales. For example, before the Covid-19 period, the (log s*) ≈ 6.3 for consumer services, consumer goods, energy, financials, technology, utilities, (log s*) ≈ 6 for basic materials, health care, and telecommunications for both stock markets. However, for industrial stock, (log s*) ≈ 6.3 for the conventional stock market and 6 for the Islamic stock market. Whereas, in the case of the Covid-19 period, (log s*) ≈ 3.4 for both DJIM stock markets'. The reason behind differences in crossover scales is the time-series changes at different scales of time. Therefore, the MF-DFA applies on two different time scales, i.e., short-run and long-run. The s < s* represent the short term, whereas s > s* represents the long DJIM conventional and Islamic market dynamics.

After identifying the crossover, we compute the values of H (q) (generalized Hurst exponent). The H (q) for the DJIM conventional and sectoral markets for the short and long run before the COVID-19 period is presented in Table 3 and Table 4. The upper and lower bound values of q are −5 to +5. If the value of q is less than 0, i.e., q < 0, it depicts the small fluctuations. Whereas, if the value of q is greater than 0, i.e., q > 0, it represents the large fluctuations. The H(q) varies with the value of q implies that multifractality exists in both the long and short run. The value of h(q) is different from 0.5, and both conventional and Islamic sectoral markets do not display a

**Table 2**
Descriptive statistics and results of unit root test of return series for the COVID-19 period.

| | Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | J-B | ADF test |
|---|---|---|---|---|---|---|---|---|
| **Sectoral Stock (Islamic)** | | | | | | | | |
| Basic Materials | 0.00004 | 0.04222 | −0.04533 | 0.00582 | −0.88635 | 15.21388 | 4271.343*** | −16.536*** |
| Consumer Services | 0.00002 | 0.03960 | −0.05601 | 0.00683 | −1.26222 | 15.43257 | 4513.068*** | −16.686*** |
| Consumer Goods | 0.00013 | 0.02481 | −0.04052 | 0.00523 | −0.96754 | 11.04089 | 1918.062*** | −16.957*** |
| Energy | 0.00004 | 0.05856 | −0.08192 | 0.01001 | −1.20375 | 15.74148 | 4714.960*** | −20.035*** |
| Financials | 0.00012 | 0.04788 | −0.05963 | 0.00727 | −0.56015 | 15.89319 | 4696.686*** | −17.979*** |
| Health Care | 0.00008 | 0.02520 | −0.03427 | 0.00490 | −0.50645 | 10.75957 | 1717.186*** | −17.052*** |
| Industrials | 0.00011 | 0.03944 | −0.04163 | 0.00577 | −0.76506 | 14.32847 | 3664.357*** | −17.133*** |
| Technology | 0.00023 | 0.03671 | −0.05407 | 0.00775 | −0.63317 | 9.28278 | 1151.866*** | −17.491*** |
| Telecommunications | 0.00001 | 0.01928 | −0.01738 | 0.00317 | −0.19422 | 9.29101 | 1114.032*** | −13.964*** |
| Utilities | 0.00001 | 0.01534 | −0.02456 | 0.00405 | −0.60994 | 6.80587 | 447.901*** | −16.929*** |
| **Sectoral Stock (Conventional)** | | | | | | | | |
| Basic Materials | 0.00007 | 0.04132 | −0.04847 | 0.00616 | −0.96695 | 13.96554 | 3476.689*** | −16.588*** |
| Consumer Services | 0.00003 | 0.02788 | −0.04374 | 0.00608 | −1.20484 | 12.19666 | 2534.550*** | −16.958*** |
| Consumer Goods | 0.00009 | 0.02653 | −0.04193 | 0.00504 | −1.08541 | 13.14515 | 3018.311*** | −16.769*** |
| Energy | 0.00010 | 0.06605 | −0.09117 | 0.01044 | −1.31768 | 18.37769 | 6825.862*** | −19.733*** |
| Financials | 0.00001 | 0.04565 | −0.05330 | 0.00694 | −1.19237 | 17.86230 | 6353.535*** | −16.785*** |
| Health Care | 0.00011 | 0.02711 | −0.03614 | 0.00510 | −0.60193 | 12.66390 | 2659.478*** | −17.022*** |
| Industrials | 0.00007 | 0.04139 | −0.04493 | 0.00608 | −0.87004 | 15.68719 | 4598.625*** | −17.234*** |
| Technology | 0.00024 | 0.03851 | −0.05574 | 0.00803 | −0.63146 | 9.39989 | 1193.272*** | −17.614*** |
| Telecommunications | −0.00010 | 0.01998 | −0.03858 | 0.00441 | −1.02645 | 14.84795 | 4054.496*** | −17.520*** |
| Utilities | 0.00003 | 0.03710 | −0.05200 | 0.00591 | −0.90436 | 20.33468 | 8518.006*** | −18.026*** |

Note: J-B = Jarque-Bera test of Normality, and ADF = augmented Dickey and Fuller (1979) test of stationary.*** denotes the rejection of the null hypothesis at 1%.

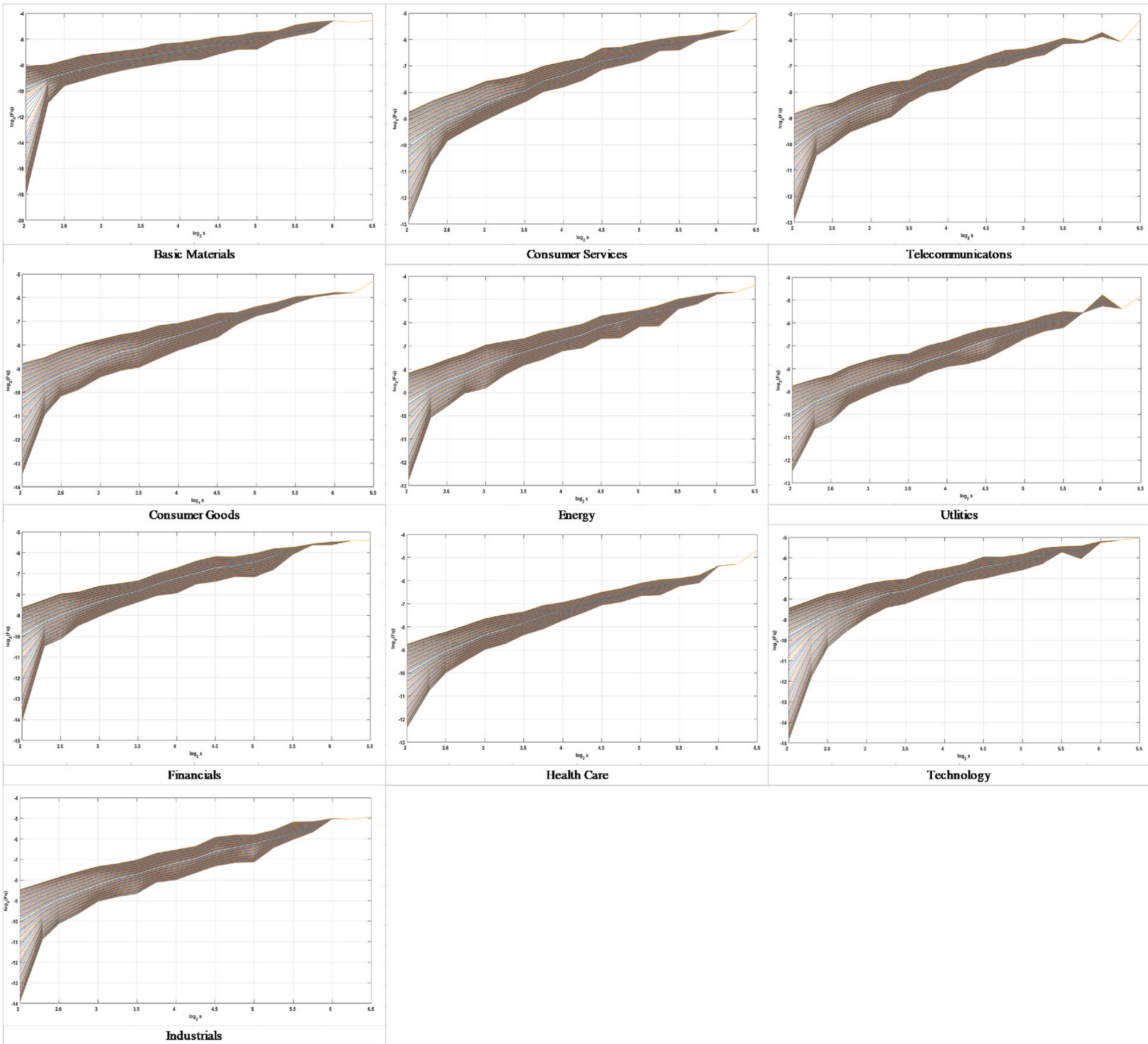


**Fig. 1.** (Islamic sectoral markets before Covid-19 period).

random walk behavior. The h(q) value for $q < 0$ is usually higher than $q > 0$, implying that both sectoral markets show long-term persistence in small fluctuations. Moreover, in the case of small fluctuations, both the sectoral stock markets are characterized by long-term memory features as the values of $h(q) > 0.5$ and $< 1$. In the short term, the sectoral market series show long-term persistence except for consumer goods, health care, technology, telecommunication in both the markets and consumer goods, and utilities in the conventional sectoral market.

At the $q = -5$, in the case of the Islamic sectoral market, the basic material sector is the most persistent in the short run, and in the long run, the utility sector is more persistent. In the case of conventional sectoral markets, the technology sector is the most persistent in the short run. In contrast, the basic materials and industrial sectors are more persistent in the long run. While focusing on the standard DFA case of $q = 2$, both the markets do not display a random walk behavior as the values of h(q) is different from 0.5. In the short term, both the sectoral market series show long-term persistence. However, both the sectoral markets show short-term persistence in the long run, which implies that investors can earn abnormal profits (Tiwari et al., 2019).

Tables 5 and 6 depict the generalized Hurst exponents during the Covid-19 period. Both the tables show that the H(q) varies with the value of q implies that multifractality exists in both the long and short run. The value of H(q) is different from 0.5, and both conventional and Islamic sectoral markets do not display a random walk behaviour. The Hurst exponent upward values are shown by H (q)+, and the downward values are shown by H(q)-.The considered sectoral stocks show long memory characteristics, especially in small fluctuations (Hq-) than in the large fluctuations (Hq+) as the values of $h(q) > 0.5$ and $< 1$. The study shows that long-term persistence and the persistence level are more critical in the short term than the long term, as it becomes lower for large

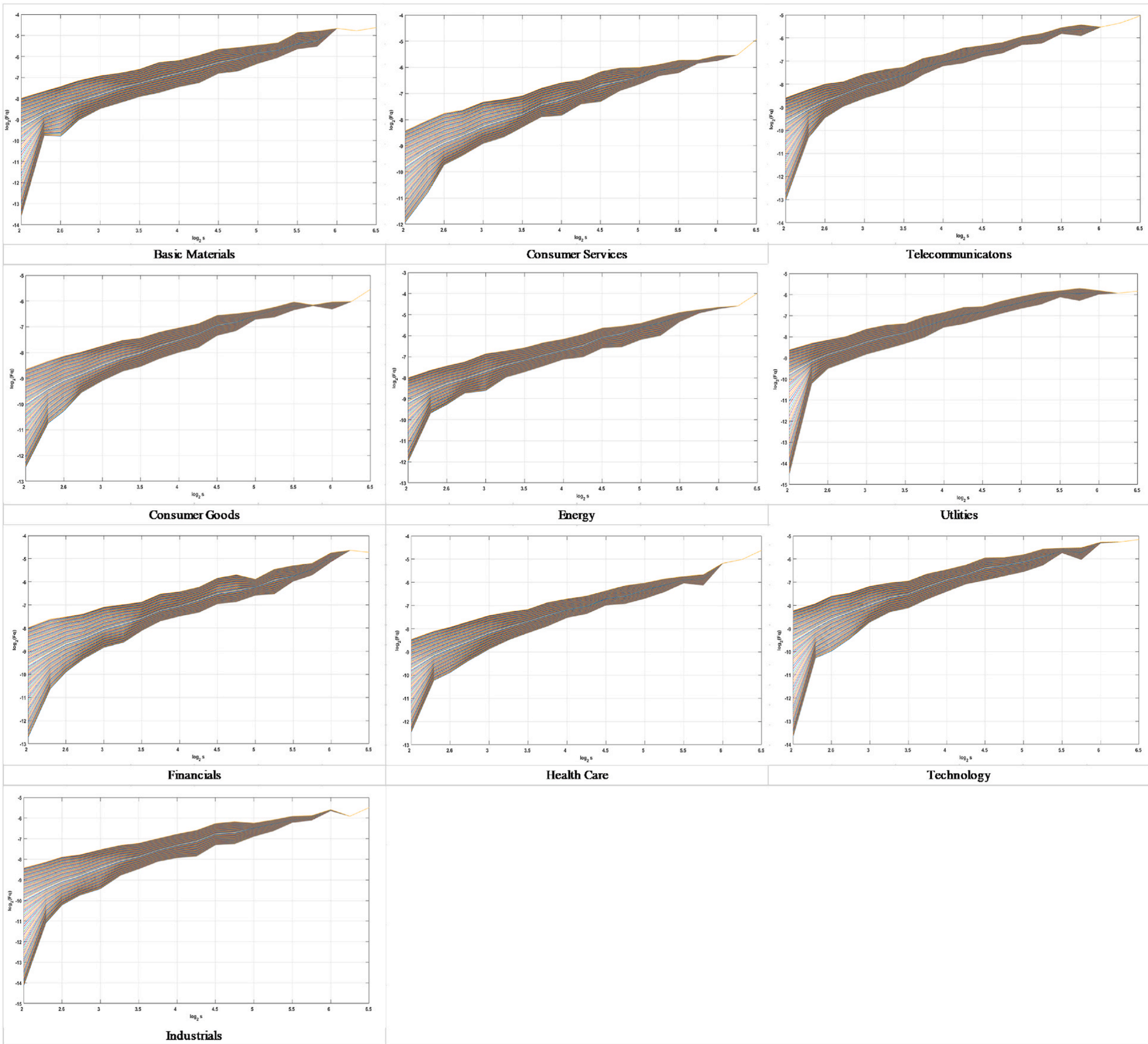


**Fig. 2.** (Conventional sectoral markets before Covid-19 period).

fluctuations (Mensi et al., 2018, 2022; Raza et al., 2021).

At the q = −5, in the case of Islamic sectoral markets, the industrials sector is the most persistent in both the short and long run. The result coincides with the Hoesli and Malle study (2021), which reported that the industrial sector is less affected by the crisis. In the case of conventional sectoral markets, energy is the most persistent in the short run and telecommunications in the long run. The outcome contrasts with the study of Alam et al. (2021). They stated that energy and telecommunication are the two most affected sectors at the time of covid due to low oil demand and high demand for services due to work-from-home policies.

Moreover, the standard DFA, i.e., case of q = 2, shows the level of persistence of sectoral markets. The result depicted in Tables 5 and 6 reflects diverse behaviour. All the Islamic sectoral stocks in the long and short run show persistent behaviour as the values are more significant than 0.5, except for financials, industrials and technology, which show anti-persistent behaviour as the values are less than 0.5 in the long run. Similarly, all the conventional sectors sectoral stocks in the long and short run show persistent behaviour as the values are more significant than 0.5, except for financials, industrials and utilities, which show anti-persistent behaviour as the values are less than 0.5 in the long run. The persistent behaviour implies that another positive trend will likely follow a positive return in those sectors. In contrast, another negative return follows a negative return in those sectors and then reverts (Aslam et al., 2021, 2022).

Moreover, the anti-persistent behaviour of the sectors depicts the negative autocorrelation implying that any change (positive or negative) in the last timeframe would follow an opposite pattern in the current period (Aslam et al., 2020). To conclude, the depiction of short-term persistence implies that investors can earn abnormal profits by predicting the stock returns by using this anti-persistent

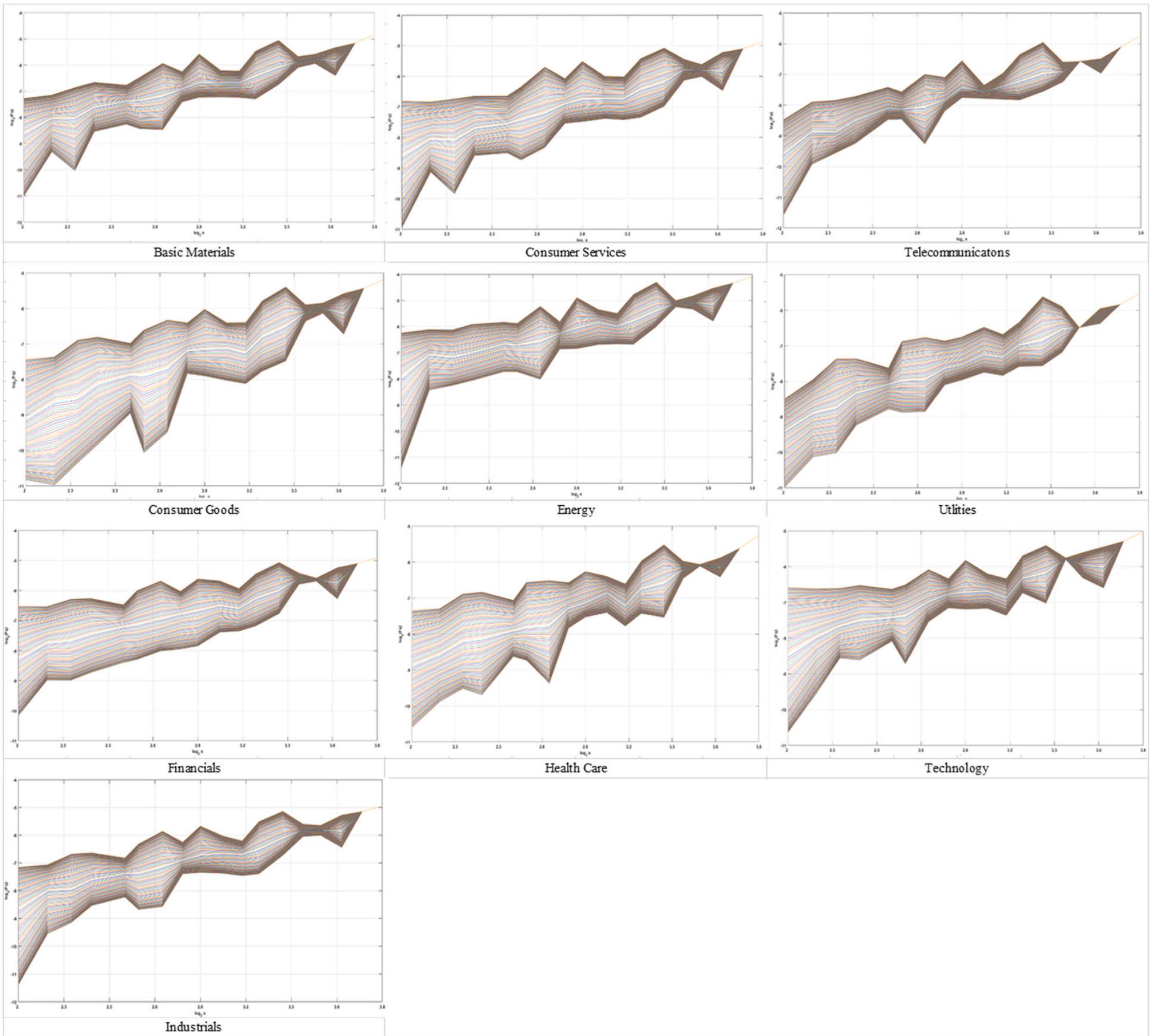


**Fig. 3.** (Islamic sectoral markets during Covid-19 period).

information. Thus, this anti-persistency provides an arbitrage opportunity for investors (Tiwari et al., 2019).

The market deficiency measure (MDM) is used to analyze the efficiency of the DJIM conventional and sectoral markets. Table 7 shows both sectoral markets' market deficiency measure (MDM) before the Covid-19 period. The market considers efficient if the value is zero and inefficient if the value is high (Mensi et al., 2017). The table shows that in the Islamic sectoral market, the consumer services sector is the most efficient in both runs. On the other hand, in the conventional sectoral market, the consumer services sector is the most efficient in the short run and the consumer goods sector in the long run. Table 8 shows both sectoral markets' market deficiency measures (MDM) during the Covid-19 period. From the table, it is observed that in the Islamic sectoral market, the health care sector is the most efficient in the short run, which coincides with the study of González et al. (2019), and the financial sector is the most efficient in the long run. Whereas, in the conventional sectoral market, the financial sector is the most efficient in the short run, and the utility sector is the most efficient in the long run, coinciding with the study of Alam et al. (2016).

## 5. Conclusion

This study uses the MF-DFA technique to examine the market efficiency of conventional and DJIM sectoral stock markets before and during the Covid-19 period. To this end, we used the MFDFA and generalized Hurst exponent and drew a comparison of market efficiency between small and large fluctuations and short- and long-run horizons. The findings of the result are summarized as follows. Firstly, the technique confirms the existence of multifractality in the data. Secondly, both conventional and Islamic sectoral stock

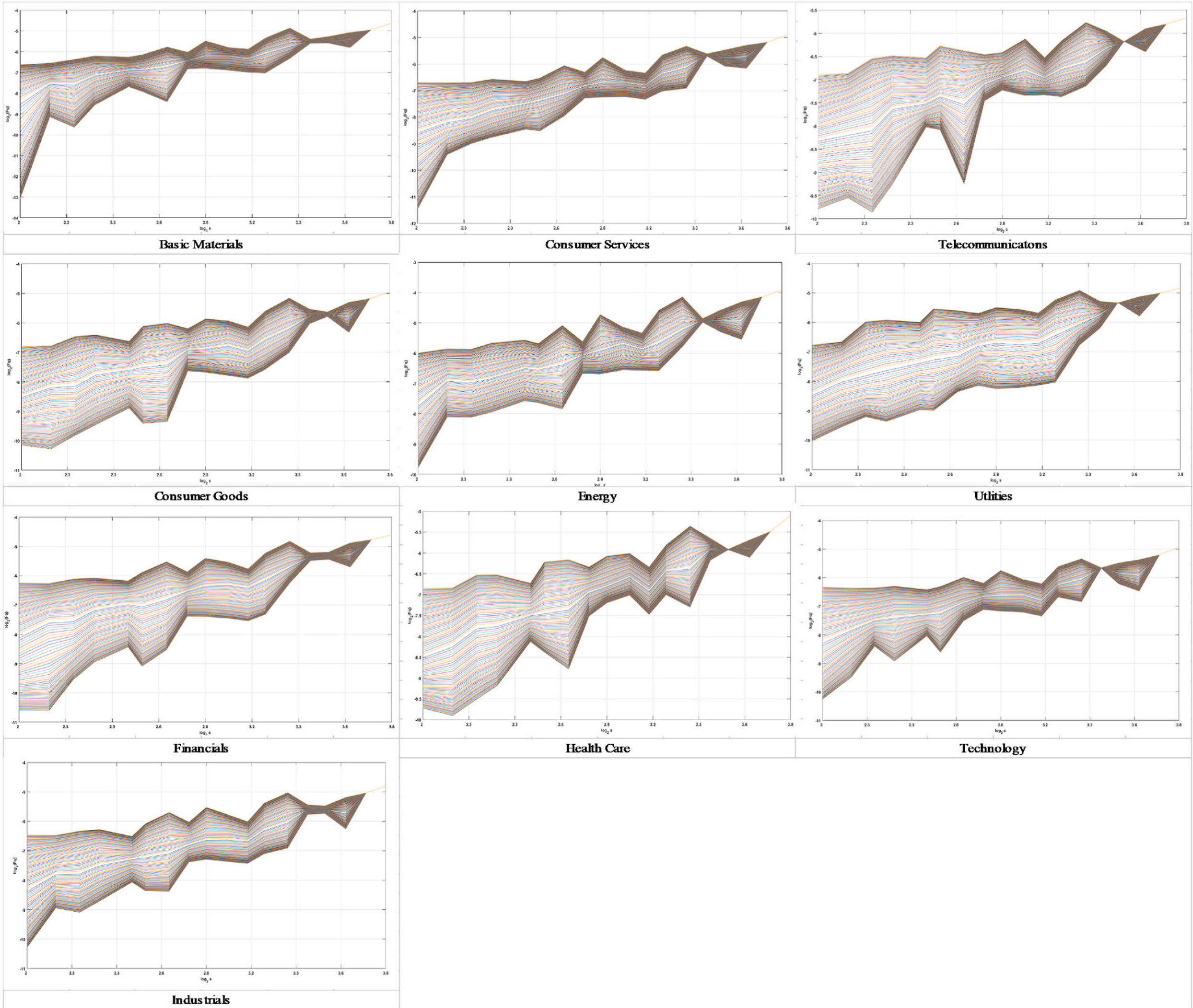


**Fig. 4.** (Conventional sectoral markets during Covid-19 period).

markets are characterized by long-term memory features in small fluctuations before and during the Covid-19 period. Thirdly, in terms of efficiency before the Covid-19 period, in the Islamic sectoral market, the health care sector is the most efficient in the short run, and the financial sector is the most efficient in the long run. Whereas during the Covid-19 period, in the conventional sectoral market, the financial sector is the most efficient in the short run, and the utility sector is the most efficient in the long run.

The result confirms that the efficiency varies over time, and some sectoral markets are more efficient in the long run and some in the short run. These findings give valuable implications to the portfolio investors, regulators, policymakers, and researchers. It is evident from the results that both conventional and DJIM sectoral stock markets have multifractal features, and thus the price movements of these indices can be used to predict price and earn high profits. It suggests that the investors should pay more attention to DJIM stock markets' multi-scale features while diversifying their portfolios. It is because some opportunities are available in the long run but not in the short run.

It is also observed that some traditional sectoral markets are inefficient and provide arbitrage opportunities for investors to earn abnormal profits contradicting securities' fair values. This inefficiency allows the market to improve through policies and decisions that will help market development, making them more efficient. It can be enhanced by encouraging the transparent flow of information, better trading technology, and more active investment strategies based on good regulatory institutions and efficiency levels. All these outcomes help investors earn risk-adjusted returns, and firms receive a fair value for their securities. Furthermore, the results also support policymakers in maintaining Islamic stock market stability. The outcome also helps the investment industry rebalance its portfolios and improves asset allocation. It is also suggested that the researcher include multifractality features while forecasting crashes and stock volatility.

**Table 3**
Generalized Hurst exponents of Islamic sectoral stocks for short and long-term components from −5 to 5 before the COVID-19 period.

| Sector | Basic Materials | | Consumer Services | | Consumer Goods | | Energy | | Financials | |
|---|---|---|---|---|---|---|---|---|---|---|
| Order of q | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term |
| −5 | 2.738 | 0.637 | 1.443 | 0.482 | 1.948 | 0.643 | 1.774 | 0.586 | 1.957 | 0.591 |
| −4 | 2.614 | 0.617 | 1.322 | 0.470 | 1.815 | 0.614 | 1.666 | 0.573 | 1.844 | 0.573 |
| −3 | 2.412 | 0.595 | 1.159 | 0.457 | 1.610 | 0.582 | 1.487 | 0.558 | 1.646 | 0.551 |
| −2 | 2.038 | 0.571 | 0.969 | 0.441 | 1.308 | 0.548 | 1.210 | 0.540 | 1.308 | 0.526 |
| −1 | 1.183 | 0.547 | 0.807 | 0.424 | 0.993 | 0.513 | 0.914 | 0.520 | 0.935 | 0.497 |
| 0 | 0.799 | 0.524 | 0.699 | 0.404 | 0.819 | 0.477 | 0.744 | 0.496 | 0.763 | 0.464 |
| 1 | 0.720 | 0.501 | 0.632 | 0.382 | 0.732 | 0.442 | 0.660 | 0.471 | 0.673 | 0.430 |
| 2 | 0.665 | 0.480 | 0.589 | 0.360 | 0.671 | 0.409 | 0.615 | 0.447 | 0.608 | 0.399 |
| 3 | 0.615 | 0.459 | 0.560 | 0.339 | 0.619 | 0.379 | 0.588 | 0.424 | 0.556 | 0.373 |
| 4 | 0.570 | 0.439 | 0.539 | 0.319 | 0.575 | 0.353 | 0.571 | 0.403 | 0.515 | 0.351 |
| 5 | 0.532 | 0.421 | 0.523 | 0.301 | 0.540 | 0.331 | 0.560 | 0.385 | 0.484 | 0.334 |
| Sector | Health Care | | Industrials | | Technology | | Telecommunications | | Utilities | |
| Order of q | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term |
| −5 | 1.584 | 0.558 | 2.233 | 0.621 | 2.202 | 0.553 | 1.679 | 0.550 | 1.521 | 0.666 |
| −4 | 1.459 | 0.538 | 2.064 | 0.604 | 2.092 | 0.533 | 1.544 | 0.531 | 1.403 | 0.651 |
| −3 | 1.274 | 0.518 | 1.790 | 0.583 | 1.887 | 0.511 | 1.348 | 0.509 | 1.240 | 0.633 |
| −2 | 1.056 | 0.498 | 1.382 | 0.559 | 1.490 | 0.488 | 1.106 | 0.485 | 1.048 | 0.611 |
| −1 | 0.875 | 0.479 | 1.003 | 0.533 | 0.989 | 0.463 | 0.891 | 0.460 | 0.877 | 0.585 |
| 0 | 0.759 | 0.460 | 0.828 | 0.505 | 0.789 | 0.438 | 0.763 | 0.434 | 0.759 | 0.555 |
| 1 | 0.683 | 0.442 | 0.739 | 0.477 | 0.693 | 0.415 | 0.688 | 0.410 | 0.686 | 0.525 |
| 2 | 0.624 | 0.422 | 0.680 | 0.450 | 0.635 | 0.393 | 0.636 | 0.387 | 0.638 | 0.496 |
| 3 | 0.576 | 0.402 | 0.632 | 0.425 | 0.598 | 0.375 | 0.595 | 0.366 | 0.600 | 0.471 |
| 4 | 0.535 | 0.383 | 0.593 | 0.402 | 0.575 | 0.358 | 0.563 | 0.347 | 0.569 | 0.450 |
| 5 | 0.503 | 0.366 | 0.563 | 0.383 | 0.561 | 0.344 | 0.540 | 0.330 | 0.545 | 0.433 |

Note: The generalized Hurst exponent H (q) for the short term and the long run is presented in Table 2. The upper and lower bound values of q are −5 to +5. If the value of q is less than 0, i.e., $q < 0$, it depicts the small fluctuations. Whereas, if the value of q is greater than 0, i.e., $q > 0$, then it represents the large fluctuations. The H(q) varies with the value of q implies that multifractality exists in the short and long term.

**Table 4**
Generalized Hurst exponents of conventional sectoral stocks for short and long-term components from −5 to 5 before the COVID-19 period.

| Sector | Basic Materials | | Consumer Services | | Consumer Goods | | Energy | | Financials | |
|---|---|---|---|---|---|---|---|---|---|---|
| Order of q | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term |
| −5 | 1.987 | 0.584 | 1.353 | 0.517 | 1.649 | 0.507 | 1.457 | 0.581 | 1.694 | 0.555 |
| −4 | 1.846 | 0.568 | 1.252 | 0.503 | 1.535 | 0.489 | 1.370 | 0.570 | 1.547 | 0.543 |
| −3 | 1.621 | 0.549 | 1.122 | 0.487 | 1.355 | 0.468 | 1.228 | 0.557 | 1.327 | 0.530 |
| −2 | 1.259 | 0.529 | 0.969 | 0.469 | 1.099 | 0.444 | 1.020 | 0.542 | 1.062 | 0.517 |
| −1 | 0.875 | 0.509 | 0.821 | 0.447 | 0.855 | 0.418 | 0.806 | 0.524 | 0.856 | 0.501 |
| 0 | 0.710 | 0.488 | 0.707 | 0.423 | 0.705 | 0.391 | 0.677 | 0.503 | 0.718 | 0.483 |
| 1 | 0.634 | 0.465 | 0.628 | 0.395 | 0.619 | 0.365 | 0.607 | 0.478 | 0.615 | 0.462 |
| 2 | 0.591 | 0.440 | 0.577 | 0.365 | 0.559 | 0.339 | 0.566 | 0.452 | 0.537 | 0.439 |
| 3 | 0.565 | 0.414 | 0.545 | 0.336 | 0.509 | 0.316 | 0.542 | 0.427 | 0.480 | 0.417 |
| 4 | 0.550 | 0.390 | 0.522 | 0.309 | 0.467 | 0.296 | 0.530 | 0.405 | 0.440 | 0.396 |
| 5 | 0.539 | 0.369 | 0.504 | 0.285 | 0.432 | 0.278 | 0.523 | 0.385 | 0.411 | 0.378 |
| Sector | Health Care | | Industrials | | Technology | | Telecommunications | | Utilities | |
| Order of q | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term |
| −5 | 1.501 | 0.531 | 2.106 | 0.584 | 2.280 | 0.490 | 1.826 | 0.467 | 2.186 | 0.470 |
| −4 | 1.414 | 0.519 | 1.950 | 0.560 | 2.131 | 0.475 | 1.675 | 0.456 | 2.026 | 0.458 |
| −3 | 1.267 | 0.507 | 1.696 | 0.533 | 1.851 | 0.459 | 1.446 | 0.444 | 1.771 | 0.445 |
| −2 | 1.053 | 0.494 | 1.298 | 0.502 | 1.351 | 0.443 | 1.138 | 0.433 | 1.347 | 0.431 |
| −1 | 0.840 | 0.480 | 0.914 | 0.469 | 0.908 | 0.425 | 0.882 | 0.421 | 0.881 | 0.415 |
| 0 | 0.699 | 0.465 | 0.725 | 0.434 | 0.732 | 0.407 | 0.736 | 0.408 | 0.706 | 0.400 |
| 1 | 0.611 | 0.448 | 0.621 | 0.400 | 0.637 | 0.387 | 0.646 | 0.394 | 0.623 | 0.384 |
| 2 | 0.554 | 0.428 | 0.552 | 0.368 | 0.576 | 0.367 | 0.583 | 0.379 | 0.567 | 0.369 |
| 3 | 0.515 | 0.406 | 0.500 | 0.338 | 0.537 | 0.348 | 0.534 | 0.362 | 0.523 | 0.355 |
| 4 | 0.488 | 0.385 | 0.456 | 0.312 | 0.510 | 0.331 | 0.495 | 0.344 | 0.485 | 0.342 |
| 5 | 0.465 | 0.365 | 0.419 | 0.289 | 0.492 | 0.316 | 0.463 | 0.327 | 0.453 | 0.330 |

Note: The generalized Hurst exponent H (q) for the short term and the long run is presented in Table 2. The upper and lower bound values of q are −5 to +5. If the value of q is less than 0, i.e., $q < 0$, it depicts the small fluctuations. Whereas, if the value of q is greater than 0, i.e., $q > 0$, then it represents the large fluctuations. The H(q) varies with the value of q implies that multifractality exists in the short and long term.

**Table 5**
Generalized Hurst exponents of Islamic sectoral stocks for short and long-term components from −5 to 5 during the COVID-19 period.

| Sector | Basic Materials | | Consumer Services | | Consumer Goods | | Energy | | Financials | |
|---|---|---|---|---|---|---|---|---|---|---|
| Order of q | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term |
| −5 | 3.375 | 0.622 | 2.968 | 0.583 | 2.649 | 0.660 | 1.760 | 0.608 | 2.177 | 0.583 |
| −4 | 3.211 | 0.607 | 2.762 | 0.562 | 2.474 | 0.648 | 1.675 | 0.590 | 2.043 | 0.562 |
| −3 | 2.860 | 0.592 | 2.414 | 0.539 | 2.197 | 0.635 | 1.533 | 0.574 | 1.843 | 0.540 |
| −2 | 2.144 | 0.580 | 1.857 | 0.518 | 1.772 | 0.622 | 1.320 | 0.565 | 1.558 | 0.517 |
| −1 | 1.347 | 0.575 | 1.290 | 0.508 | 1.287 | 0.611 | 1.074 | 0.568 | 1.223 | 0.497 |
| 0 | 1.008 | 0.578 | 0.995 | 0.516 | 0.961 | 0.599 | 0.876 | 0.585 | 0.937 | 0.482 |
| 1 | 0.832 | 0.583 | 0.834 | 0.529 | 0.779 | 0.581 | 0.734 | 0.601 | 0.728 | 0.466 |
| 2 | 0.720 | 0.574 | 0.680 | 0.524 | 0.654 | 0.551 | 0.618 | 0.593 | 0.552 | 0.438 |
| 3 | 0.645 | 0.547 | 0.529 | 0.500 | 0.547 | 0.511 | 0.533 | 0.561 | 0.400 | 0.399 |
| 4 | 0.591 | 0.515 | 0.413 | 0.470 | 0.458 | 0.473 | 0.489 | 0.524 | 0.291 | 0.360 |
| 5 | 0.549 | 0.486 | 0.336 | 0.443 | 0.392 | 0.441 | 0.475 | 0.492 | 0.217 | 0.328 |
| Sector | Health Care | | Industrials | | Technology | | Telecommunications | | Utilities | |
| Order of q | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term |
| −5 | 1.538 | 0.583 | 4.868 | 0.682 | 4.160 | 0.591 | 2.743 | 0.547 | 2.777 | 0.675 |
| −4 | 1.476 | 0.568 | 4.640 | 0.663 | 3.933 | 0.571 | 2.599 | 0.530 | 2.591 | 0.660 |
| −3 | 1.390 | 0.551 | 4.210 | 0.641 | 3.511 | 0.548 | 2.354 | 0.518 | 2.288 | 0.643 |
| −2 | 1.282 | 0.538 | 3.340 | 0.615 | 2.659 | 0.525 | 1.940 | 0.514 | 1.850 | 0.626 |
| −1 | 1.156 | 0.535 | 1.778 | 0.587 | 1.443 | 0.505 | 1.394 | 0.523 | 1.378 | 0.609 |
| 0 | 1.010 | 0.553 | 0.978 | 0.557 | 0.930 | 0.494 | 1.021 | 0.540 | 1.019 | 0.590 |
| 1 | 0.855 | 0.578 | 0.760 | 0.524 | 0.740 | 0.489 | 0.861 | 0.545 | 0.779 | 0.563 |
| 2 | 0.694 | 0.578 | 0.626 | 0.483 | 0.603 | 0.485 | 0.777 | 0.520 | 0.575 | 0.524 |
| 3 | 0.536 | 0.551 | 0.508 | 0.437 | 0.468 | 0.475 | 0.695 | 0.474 | 0.361 | 0.477 |
| 4 | 0.409 | 0.517 | 0.411 | 0.395 | 0.338 | 0.461 | 0.605 | 0.427 | 0.164 | 0.432 |
| 5 | 0.322 | 0.486 | 0.340 | 0.361 | 0.230 | 0.445 | 0.524 | 0.390 | 0.019 | 0.395 |

Note: The generalized Hurst exponent H (q) for the short term and the long run is presented in Table 2. The upper and lower bound values of q are −5 to +5. If the value of q is less than 0, i.e., $q < 0$, it depicts the small fluctuations. Whereas, if the value of q is greater than 0, i.e., $q > 0$, then it represents the large fluctuations. The H(q) varies with the value of q implies that multifractality exists in the short and long term.

**Table 6**
Generalized Hurst exponents of conventional sectoral stocks for short and long-term components from −5 to 5 during the COVID-19 period.

| Sector | Basic Materials | | Consumer Services | | Consumer Goods | | Energy | | Financials | |
|---|---|---|---|---|---|---|---|---|---|---|
| Order of q | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term |
| −5 | 2.696 | 0.585 | 3.608 | 0.547 | 1.951 | 0.585 | 4.051 | 0.634 | 1.914 | 0.661 |
| −4 | 2.537 | 0.575 | 3.413 | 0.527 | 1.889 | 0.573 | 3.829 | 0.619 | 1.808 | 0.638 |
| −3 | 2.257 | 0.566 | 3.047 | 0.507 | 1.770 | 0.561 | 3.433 | 0.606 | 1.655 | 0.614 |
| −2 | 1.817 | 0.560 | 2.365 | 0.489 | 1.566 | 0.553 | 2.669 | 0.598 | 1.458 | 0.593 |
| −1 | 1.353 | 0.559 | 1.484 | 0.485 | 1.293 | 0.553 | 1.530 | 0.598 | 1.228 | 0.583 |
| 0 | 1.047 | 0.567 | 1.006 | 0.503 | 1.047 | 0.565 | 0.960 | 0.607 | 0.993 | 0.585 |
| 1 | 0.864 | 0.578 | 0.821 | 0.530 | 0.874 | 0.574 | 0.767 | 0.607 | 0.793 | 0.586 |
| 2 | 0.752 | 0.576 | 0.693 | 0.539 | 0.744 | 0.561 | 0.647 | 0.581 | 0.616 | 0.565 |
| 3 | 0.679 | 0.555 | 0.561 | 0.527 | 0.632 | 0.528 | 0.568 | 0.533 | 0.450 | 0.529 |
| 4 | 0.625 | 0.525 | 0.448 | 0.506 | 0.542 | 0.492 | 0.533 | 0.486 | 0.324 | 0.493 |
| 5 | 0.582 | 0.496 | 0.372 | 0.484 | 0.476 | 0.461 | 0.523 | 0.450 | 0.239 | 0.463 |
| Sector | Health Care | | Industrials | | Technology | | Telecommunications | | Utilities | |
| Order of q | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term | Short-term | Long-term |
| −5 | 2.121 | 0.578 | 3.201 | 0.640 | 3.509 | 0.594 | 2.093 | 0.673 | 2.130 | 0.618 |
| −4 | 1.946 | 0.561 | 2.986 | 0.621 | 3.265 | 0.573 | 2.029 | 0.654 | 1.996 | 0.605 |
| −3 | 1.707 | 0.544 | 2.620 | 0.601 | 2.844 | 0.549 | 1.869 | 0.633 | 1.765 | 0.591 |
| −2 | 1.436 | 0.529 | 2.032 | 0.579 | 2.104 | 0.525 | 1.563 | 0.612 | 1.437 | 0.578 |
| −1 | 1.201 | 0.528 | 1.367 | 0.557 | 1.267 | 0.507 | 1.218 | 0.591 | 1.113 | 0.570 |
| 0 | 1.020 | 0.550 | 0.962 | 0.535 | 0.892 | 0.496 | 0.974 | 0.569 | 0.865 | 0.562 |
| 1 | 0.868 | 0.584 | 0.749 | 0.509 | 0.717 | 0.492 | 0.803 | 0.542 | 0.670 | 0.536 |
| 2 | 0.721 | 0.587 | 0.601 | 0.472 | 0.583 | 0.486 | 0.674 | 0.506 | 0.522 | 0.475 |
| 3 | 0.581 | 0.556 | 0.475 | 0.426 | 0.453 | 0.475 | 0.585 | 0.462 | 0.439 | 0.403 |
| 4 | 0.471 | 0.519 | 0.374 | 0.383 | 0.328 | 0.459 | 0.525 | 0.421 | 0.396 | 0.348 |
| 5 | 0.397 | 0.486 | 0.302 | 0.349 | 0.225 | 0.441 | 0.484 | 0.389 | 0.372 | 0.309 |

Note: The generalized Hurst exponent H (q) for the short term and the long run is presented in Table 2. The upper and lower bound values of q are −5 to +5. If the value of q is less than 0, i.e., $q < 0$, it depicts the small fluctuations. Whereas, if the value of q is greater than 0, i.e., $q > 0$, then it represents the large fluctuations. The H(q) varies with the value of q implies that multifractality exists in the short and long term.

**Table 7**
MF-DFA rankings for short and long-term components before the COVID-19 period.

| Sectoral Stock (Islamic) | | | | | |
|---|---|---|---|---|---|
| Short-term | | | Long-term | | |
| Ranking | Sector | MDM | Ranking | Sector | MDM |
| 1 | Consumer Services | 0.930 | 1 | Consumer Services | 0.424 |
| 2 | Utilities | 0.986 | 2 | Telecommunications | 0.439 |
| 3 | Health Care | 0.997 | 3 | Technology | 0.446 |
| 4 | Telecommunications | 1.053 | 4 | Health Care | 0.461 |
| 5 | Energy | 1.119 | 5 | Financials | 0.462 |
| 6 | Financials | 1.180 | 6 | Consumer Goods | 0.483 |
| 7 | Consumer Goods | 1.195 | 7 | Energy | 0.488 |
| 8 | Industrials | 1.328 | 8 | Industrials | 0.503 |
| 9 | Technology | 1.333 | 9 | Basic Materials | 0.528 |
| 10 | Basic Materials | 1.592 | 10 | Utilities | 0.551 |
| **Sectoral Stock (Conventional)** | | | | | |
| Short-term | | | Long-term | | |
| Ranking | Sector | MDM | Ranking | Sector | MDM |
| 1 | Consumer Services | 0.887 | 1 | Consumer Goods | 0.403 |
| 2 | Energy | 0.950 | 2 | Consumer Services | 0.406 |
| 3 | Health Care | 0.951 | 3 | Technology | 0.428 |
| 4 | Financials | 0.994 | 4 | Industrials | 0.436 |
| 5 | Consumer Goods | 1.001 | 5 | Utilities | 0.442 |
| 6 | Telecommunications | 1.085 | 6 | Telecommunications | 0.444 |
| 7 | Basic Materials | 1.198 | 7 | Health Care | 0.452 |
| 8 | Industrials | 1.203 | 8 | Financials | 0.469 |
| 9 | Utilities | 1.255 | 9 | Basic Materials | 0.479 |
| 10 | Technology | 1.321 | 10 | Energy | 0.487 |

Note: This table shows the market deficiency measure (MDM) of all the economies in the full sample, before the global financial crisis and after the global financial crisis. The market is considered efficient if the value is zero and inefficient if the value is high.

**Table 8**
MF-DFA rankings for short and long-term components during the COVID-19 period.

| Sectoral Stock (Islamic) | | | | | |
|---|---|---|---|---|---|
| Short-term | | | Long-term | | |
| Ranking | Sector | MDM | Ranking | Sector | MDM |
| 1 | Health Care | 0.943 | 1 | Financials | 0.461 |
| 2 | Energy | 1.082 | 2 | Telecommunications | 0.479 |
| 3 | Financials | 1.167 | 3 | Consumer Services | 0.516 |
| 4 | Utilities | 1.377 | 4 | Technology | 0.516 |
| 5 | Consumer Goods | 1.466 | 5 | Health Care | 0.529 |
| 6 | Consumer Services | 1.588 | 6 | Industrials | 0.542 |
| 7 | Telecommunications | 1.602 | 7 | Utilities | 0.546 |
| 8 | Basic Materials | 1.901 | 8 | Energy | 0.557 |
| 9 | Technology | 2.136 | 9 | Consumer Goods | 0.560 |
| 10 | Industrials | 2.525 | 10 | Basic Materials | 0.561 |
| **Sectoral Stock (Conventional)** | | | | | |
| Short-term | | | Long-term | | |
| Ranking | Sector | MDM | Ranking | Sector | MDM |
| 1 | Financials | 1.066 | 1 | Utilities | 0.476 |
| 2 | Utilities | 1.196 | 2 | Health Care | 0.502 |
| 3 | Health Care | 1.208 | 3 | Technology | 0.516 |
| 4 | Consumer Goods | 1.215 | 4 | Consumer Services | 0.517 |
| 5 | Telecommunications | 1.277 | 5 | Consumer Goods | 0.533 |
| 6 | Basic Materials | 1.581 | 6 | Telecommunications | 0.538 |
| 7 | Industrials | 1.680 | 7 | Industrials | 0.540 |
| 8 | Technology | 1.796 | 8 | Basic Materials | 0.550 |
| 9 | Consumer Services | 1.930 | 9 | Energy | 0.553 |
| 10 | Energy | 2.181 | 10 | Financials | 0.565 |

Note: This table shows the market deficiency measure (MDM) of all the economies in the full sample, before the global financial crisis and after the global financial crisis. The market is considered efficient if the value is zero and inefficient if the value is high.

## Declaration of competing interest

This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal's policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare.

## References


Alam, M.M., Wei, H., Wahid, A.N., 2021. COVID-19 outbreak and sectoral performance of the Australian stock market: an event study analysis. Aust. Econ. Pap. 60 (3), 482–495.

Alam, N., Arshad, S., Rizvi, S.A.R., 2016. Do Islamic stock indices perform better than conventional counterparts? An empirical investigation of sectoral efficiency. Rev. Financ. Econ. 31, 108–114.

Al-Awadhi, A.M., Al-Saifi, K., Al-Awadhi, A., Alhamadi, S., 2020. Death and contagious infectious diseases: impact of the COVID-19 virus on stock market returns. Journal of Behavioral and Experimental Finance, 100326.

Alfaro, L., Chari, A., Greenland, A.N., Schott, P.K., 2020. Aggregate and firm-level stock returns during pandemics, in real time (No. w26950). National Bureau of Economic Research.

Ali, S., Shahzad, S.J.H., Raza, N., Al-Yahyaee, K.H., 2018. Stock market efficiency: a comparative analysis of Islamic and conventional stock markets. Phys. Stat. Mech. Appl. 503, 139–153.

Al-Khazali, O., Mirzaei, A., 2017. Stock market anomalies, market efficiency and the adaptive market hypothesis: evidence from Islamic stock indices. J. Int. Financ. Mark. Inst. Money 51, 190–208.

Arshad, S., Rizvi, S.A.R., Ghani, G.M., Duasa, J., 2016. Investigating stock market efficiency: a look at OIC member countries. Res. Int. Bus. Finance 36, 402–413.

Ashraf, B.N., 2020. Stock markets' reaction to COVID-19: cases or fatalities? Res. Int. Bus. Finance, 101249.

Aslam, F., Ferreira, P., Ali, H., Kauser, S., 2022. Herding behavior during the COVID-19 pandemic: a comparison between Asian and European stock markets based on intraday multifractality. Eurasian Economic Review 12 (2), 333–359.

Aslam, F., Mohti, W., Ferreira, P., 2020. Evidence of intraday multifractality in European stock markets during the recent coronavirus (COVID-19) outbreak. Int. J. Financ. Stud. 8 (2), 31.

Aslam, F., Nogueiro, F., Brasil, M., Ferreira, P., Mughal, K.S., Bashir, B., Latif, S., 2021. The footprints of COVID-19 on Central Eastern European stock markets: an intraday analysis. Post Commun. Econ. 33 (6), 751–769.

Cao, G., Cao, J., Xu, L., 2013. Asymmetric multifractal scaling behavior in the Chinese stock market: based on asymmetric MF-DFA. Phys. A Stat. Mech. Appl. 392 (4), 797–807.

Chen, Z., Ivanov, P.C., Hu, K., Stanley, H.E., 2002. Effect of nonstationarities on detrended fluctuation analysis. Phys. Rev. E 65 (4), 041107.

Corbet, S., Larkin, C., Lucey, B., 2020. The contagion effects of the covid-19 pandemic: evidence from gold and cryptocurrencies. Finance Res. Lett., 101554

Dickey, D.A., Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74 (366a), 427-431.

Di Matteo, T., Aste, T., Dacorogna, M.M., 2003. Scaling behaviors in differently developed markets. Phys. A Stat. Mech. Appl. 324 (1–2), 183–188.

Dunford, D., Dale, Becky, Nassos, Stylianou, Ed Lowther, Ahmed M., Arenas IdlT, 2020. Coronavirus: the World in Lockdown in Maps and Charts. BBC News. https://www.bbc.com/news/world-52103747.

González, M.D.L.O., Jareño, F., El Haddouti, C., 2019. Sector portfolio performance comparison between islamic and conventional stock markets. Sustainability 11 (17), 4618.

Goodell, J.W., 2020. COVID-19 and finance: agendas for future research. Finance Res. Lett., 101512

Haddad, H.B., Mezghani, I., Al Dohaiman, M., 2020. Common Shocks, Common Transmission Mechanisms and Time-Varying Connectedness Among Dow Jones Islamic Stock Market Indices and Global Risk Factors. Economic Systems, 100760.

Hammoudeh, S., Kim, W.J., Sarafrazi, S., 2016. Sources of fluctuations in Islamic, US, EU, and Asia equity markets: the roles of economic uncertainty, interest rates, and stock indexes. Emerg. Mark. Finance Trade 52 (5), 1195–1209.

Hoesli, M., Malle, R., 2021. Commercial real estate prices and COVID-19. J. Eur. Real Estate Res. 15 (2), 295–306.

Horvatic, D., Stanley, H.E., Podobnik, B., 2011. Detrended cross-correlation analysis for non-stationary time series with periodic trends. Europhys. Lett. 94 (1), 18007.

Jawadi, F., Jawadi, N., Cheffou, A.I., 2015. Are Islamic stock markets efficient? A time-series analysis. Appl. Econ. 47 (16), 1686–1697.

Kantelhardt, J.W., Zschiegner, S.A., Koscielny-Bunde, E., Havlin, S., Bunde, A., Stanley, H.E., 2002. Multifractal detrended fluctuation analysis of nonstationary time series. Phys. Stat. Mech. Appl. 316 (1–4), 87–114.

Kenourgios, D., Naifar, N., Dimitriou, D., 2016. Islamic financial markets and global crises: contagion or decoupling? Econ. Modell. 57, 36–46.

Kok, S., Giorgioni, G., Laws, J., 2009. Performance of shariah-compliant indices in London and NY stock markets and their potential for diversification. Int. J. Monetary Econ. Finance 2 (3–4), 398–408.

Lin, B., Su, T., 2020. The linkages between oil market uncertainty and Islamic stock markets: evidence from quantile-on-quantile approach. Energy Econ., 104759

Mandelbrot, B.B., Fisher, A.J., Calvet, L.E., 1997. A multifractal model of asset returns.

Mensi, W., Hamdi, A., Yoon, S.M., 2018. Modelling multifractality and efficiency of GCC stock markets using the MF-DFA approach: a comparative analysis of global, regional and Islamic markets. Phys. Stat. Mech. Appl. 503, 1107–1116.

Mensi, W., Tiwari, A.K., Yoon, S.M., 2017. Global financial crisis and weak-form efficiency of Islamic sectoral stock markets: an MF-DFA analysis. Phys. Stat. Mech. Appl. 471, 135–146.

Mensi, W., Yousaf, I., Vo, X.V., Kang, S.H., 2022. Multifractality during upside/downside trends in the MENA stock markets: the effects of the global financial crisis, oil crash and COVID-19 pandemic. Int. J. Emerg. Mark.

Narayan, P.K., Phan, D.H.B., Sharma, S.S., 2019. Does Islamic stock sensitivity to oil prices have economic significance? Pac. Basin Finance J. 53, 497–512.

Ning, Y., Wang, Y., Su, C.W., 2017. How did China's foreign exchange reform affect the efficiency of foreign exchange market? Phys. Stat. Mech. Appl. 483, 219–226.

Norouzzadeh, P., Rahmani, B., 2006. A multifractal detrended fluctuation description of Iranian rial–US dollar exchange rate. Phys. Stat. Mech. Appl. 367, 328–336.

Onali, E., Goddard, J., 2009. Unifractality and multifractality in the Italian stock market. Int. Rev. Financ. Anal. 18 (4), 154–163.

Oświe, P., Kwapień, J., Drożdż, S., 2005. Multifractality in the stock market: price increments versus waiting times. Phys. A Stati. Mech. Appl. 347, 626–638.

Ozili, P.K., Arun, T., 2020. *Available at*: *SSRN 3562570* Spillover of COVID-19: impact on the Global Economy.

Papadamou, S., Fassas, A., Kenourgios, D., Dimitriou, D., 2020. Direct and Indirect Effects of COVID-19 Pandemic on Implied Stock Market Volatility: Evidence from Panel Data Analysis.

Raza, S.A., Shah, N., Guesmi, K., Msolli, B., 2022. How does COVID-19 influence dynamic spillover connectedness between cryptocurrencies? Evidence from non-parametric causality-in-quantiles techniques. Finance Res. Lett. 47, 102569.

Raza, S.A., Shah, N., Suleman, M.T., Al Mamun, M., 2021. A multifractal detrended fluctuation analysis of housing market: a role of financial crises in developed economies. Int. J. Hous. Mark. Anal.

Rizvi, S.A.R., Dewandaru, G., Bacha, O.I., Masih, M., 2014. An analysis of stock market efficiency: developed vs Islamic stock markets using MF-DFA. Phys. Stat. Mech. Appl. 407, 86–99.

Singh, M.K., Neog, Y., 2020. Contagion effect of COVID-19 outbreak: another recipe for disaster on Indian economy. J. Publ. Aff., e2171

Tiwari, A.K., Aye, G.C., Gupta, R., 2019. Stock market efficiency analysis using long spans of data: a multifractal detrended fluctuation approach. Finance Res. Lett. 28, 398–411.

Wang, Y., Wu, C., Pan, Z., 2011. Multifractal detrending moving average analysis on the US Dollar exchange rates. Phys. Stat. Mech. Appl. 390 (20), 3512–3523.

Yuandong, S., Khaskheli, A., Raza, S.A., Yousufi, S.Q., 2022. How COVID-19 influences prices of oil and precious metals: comparison between data extracted from online searching trends and actual events. Resour. Pol. 78, 102916.
Zhang, D., Hu, M., Ji, Q., 2020. Financial Markets under the Global Pandemic of COVID-19. Finance Research Letters, 101528.
Zhou, W.X., 2009. The components of empirical multifractality in financial returns. Europhys. Lett. 88 (2), 28004.