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Influence of the Russia–Ukraine War and COVID-19 Pandemic on the Efficiency and Herding Behavior of Stock Markets: Evidence from G20 Nations

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Abstract: Efficiency in stock markets is essential for economic stability and growth. This study investigates the efficiency and herding behavior of the stock markets from the top economies of the world (known as G20 countries). We classify stock market indices using MSCI classification for the developed and emerging markets to provide a comparative examination using the latest data and by employing the robust multifractal detrended fluctuation (MFDFA) method. In addition to the full sample, the analysis uses sub-sample periods to reveal the hidden features and efficiencies of the G20 markets during the Russia–Ukraine War and COVID-19 for the first time. The findings show the availability of varied multifractality among all G20 stock markets during the overall and crisis periods, exhibit long-range correlations, and may support the fractal market hypothesis. In addition, Italy remains the least efficient, while Germany remains the most efficient stock market. The sub-sample results further reveal unevenness in the local fluctuations and resultant higher inefficiency considering the sheer magnitude and impact of crises on the G20 stock markets. However, the efficiency of developed stock markets performed better as compared to emerging markets. The study of G20 stock markets is useful and provides several implications for a wider audience.

Keywords: multifractal analysis; geopolitical risk; efficiency; herd behavior; COVID-19; war

JEL Classification: F36; G14; G15; N20; O16; P34

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1. Introduction

Stock price analysis is a challenging phenomenon, and numerous methods have been produced in a limitless stream. The noise and volatility characteristics of the stock market are often a reflection of various factors, and it is the distinct behavior of investors that makes stock markets quite complicated. Therefore, the sudden and continual changes in stock prices provide a platform for speculations and risks that may lead to economic losses for investors and affect economic stability (Chang et al. 2017; Sezgin Alp et al. 2022).

Previous studies follow analysis and assumptions based on the efficient market hypothesis (EMH), which assumes markets to be efficient, and the prices follow a Brownian motion known as random walk (Fama 1965, 1970). However, the rapid emergence of fractal and chaos theories has allowed for the exploration of new dimensions and has managed to overcome the weaknesses posed by the EMH. In addition, Stock markets are nonlinear by nature, and the variations in prices can be classified by turbulent and fractal behavior

(Memon et al. 2022). We use multifractal detrended fluctuation analysis (MFDFA) proposed by (Kantelhardt et al. 2002) that has served as a key tool in exploring the multifractal behavior of the non-stationary time series. In the context of the stock market index, a barometer of overall market behavior, the robust tool of MFDFA provides assistance to determine the availability of long-range dependencies incorporating with the EMH and shows the level of inefficiency (Podobnik and Stanley 2008). MFDFA has been employed by several researchers to study structural features and to explore the efficiency levels of various financial markets (Mali and Mukhopadhyay 2014; Mnif and Jarboui 2021; Memon et al. 2023) and more specifically stock markets of different regions including Europe (Caraiani 2012; Tiwari et al. 2019), Asia (Wang et al. 2009; Rizvi and Arshad 2016; Zhu and Zhang 2018), and America (Wang et al. 2014). However, there is an obstacle in the way of studying the behaviors and comparing the efficiencies of Group of Twenty (G20) stock markets.

The ongoing conflict between Russia and Ukraine has tremendous implications that expand further than the realm of geopolitics. On the one hand, it is affecting the pricing efficiency of stock markets, which is restricted to the combination of several aspects, including geopolitical uncertainty, economic instability, and investor sentiments. Upon the occurrence of conflicts, market participants often become uncertain about the future trajectory of events, including potential economic sanctions, trade disruptions, or military escalations. Therefore, uncertainty can lead to increased volatility and decreased liquidity in stock markets. Investor sentiment, influenced by the ongoing conflict, can also impact stock market efficiency. Negative sentiment driven by geopolitical tensions can lead to a flight of capital from the affected region. As a result, stock prices may deviate from their intrinsic values, making it challenging for markets to efficiently allocate capital. Moreover, the Russia–Ukraine War can cause a spillover effect beyond the region, due to the connectedness of financial markets. Conflicts and crises events are severe factors that affect economies, specifically financial markets. Due to heavy reliance on information technology, investors from all around the world can easily trade, and financial markets have become more subtle to the revelation of shocks. There are many ways this geopolitical risk (GPR) can affect financial markets. First, due to external shocks, GPR investors become more reluctant to trade in financial markets and eventually prolong the decision-making process. Second, GPR can exert panic among market participants, which eventually alters the demand and supply mechanism. Third, firms exposed to GPR and conflicts incur a high cost of operations and therefore are unable to survive for a long period. Therefore, investors and policymakers consider conflict and GPR events seriously, and numerous studies have been conducted that examine the impact of wars, conflicts, and military assaults (Bloom 2009; Schneider and Troeger 2006; Balcilar et al. 2018; Wang et al. 2021; Hudson and Urquhart 2022; Zaremba et al. 2022).

Financial constancy in stock markets is a prerequisite for assuring investment efficacy and safety, and many financial innovation techniques are utilized to effectively evaluate market efficiency. While investigating the efficiency of the Russian stock market, Ikeda (2018) used the MFDFA method to endure financial crises. In addition to finding multifractal structures of the Russian stock market, his results also showed deteriorating structures of the Russian stock market during the 1998 Russian crisis and the global financial crisis of 2008. Similarly, Arshad et al. (2016) used MFDFA to assess the efficiency of eleven Organization of Islamic Conference (OIC) member countries and found higher efficiency during the economic boom compared with lower efficiency during the crisis period. (Miloş et al. 2020) applied the MFDFA method when studying seven central and eastern European stock markets till August 2018, and their results found long-range correlation while supporting evidence of inefficient stock markets. In addition, Alam et al. (2016) performed a comparative analysis of ten global and Islamic stock indices using MFDFA. Their results demonstrated a higher efficiency of Islamic sectoral indices in comparison with conventional stock indices. Moreover, the MFDFA technique was also employed by Balasubramanian (2020) to inspect the herding behavior of the Indian stock market.

Their results found no herding or bubble in the market during the catastrophic event of demonetization in the country.

A few studies have examined the efficiency of financial markets regarding the global pandemic. Xu et al. (2021) performed time-varying multifractal analysis of the Chinese stock market around COVID-19 and found the Chinese stock market to be affected by the pandemic. Choi (2021) used the MFDFA method to analyze the efficiency of 11 US stock market sectors during crisis periods. In addition to categorizing sectors with low market efficiency, his results report that consumer discretionary and utilities sectors carry the highest and lowest levels of efficiency during crisis periods. (Mnif et al. 2020) studied five cryptocurrencies using the MFDFA method and showed herding behavior and multifractal structures before the COVID-19 period. However, all cryptocurrencies became highly efficient after the spread of the pandemic, indicating that the best possible strategies can be devised to deal with a pandemic-related financial crisis. Mensi et al. (2020) investigated the multifractality of gold and oil prices using asymmetric multifractal detrended fluctuation analysis (A-MFDFA), and their results confirmed inefficiency in the gold and oil markets due to the uncertainty created from the outbreak. Recently, Aslam et al. (2020b) performed fractal analysis of the foreign exchange market using MFDFA between October 2019 and March 2020. They also found a decline in efficiency along with lower volatility for foreign exchange markets during COVID-19. From the literature, it is evident that the MFDFA method is an important and vital tool in examining the efficiency of financial markets. In addition, there is a need to explore G20 stock markets, which represent the world's largest economies, during the overall and crisis periods of the global pandemic (COVID-19) and Russia–Ukraine War and to better comprehend the behavior of these stock markets.

In the present work, we thoroughly examine the multifractal properties of stock market indices of the Group of Twenty (G20 countries. The member countries of the G20 account for higher than 80 percent of world's GDP, thus constituting both developed and emerging stock markets. Our paper fills the existing gap in the literature in many ways. First, owing to the great importance of market efficiency, which is critical for a better-functioning stock market and growth of the economy, this paper aims to test the efficiency of blue chip G20 stock market indices while comparing developed and emerging stock markets. The literature demonstrates higher efficiency for developed countries' stock markets in comparison with emerging stock markets (Butler and Malaikah 1992; Rizvi et al. 2014); hence, it is important to further evaluate this argument. Second, with financial markets becoming more vulnerable to the contagion, we measure the efficiency of G20 markets during the time periods of the global pandemic (COVID-19) and the recent Russia–Ukraine War, for the first time. A massive black swan event like the global pandemic (Mishra 2020), which dismantled world economies and finance, brought the movement of people to a standstill (Fernando et al. 2020), requiring fresh insights for the policymakers to set due policy responses to overcome and avoid the possible future financial crisis. Third, a powerful technique of MFDFA is applied to the G20 stock market indices during the overall and stress periods. Such a well-known methodology will capture important information about the dynamics and complexity of these stock markets. Additionally, MFDFA offers a powerful analytical tool for exploring herding behavior in stock markets by revealing multifractal properties and long-range correlations in price dynamics (Aslam et al. 2020a, 2020c; Memon et al. 2023). Moreover, MFDFA can quantify the extent and persistence of the trends resulting from synchronized trading activities among investors, providing insights into the presence of herding behavior (Aslam et al. 2021; Sun et al. 2020). Fourth, the comparative work of G20 stock markets serves as a guide for a wider audience, including investors and policymakers worldwide. Finally, the Russia–Ukraine War has had a notable impact on the pricing efficiency of stock markets. Geopolitical uncertainty, economic instability, investor sentiment, and potential spillover effects can all contribute to market inefficiencies. Therefore, it is important for investors and market participants to carefully consider the implications of this conflict and its potential repercussions on pricing accuracy, risk management, and investment strategies.

The objectives of this study are outlined in the rest of this paper as follows: Section 2 presents the data and methodology. Section 3 discusses the results, and finally conclusions are offered in Section 4.

2. Methodology and Data

2.1. Data

The data set covers 19 major stock market indices of G20 member countries categorized as developed and emerging stock markets according to Morgan Stanley Capital International (MSCI) country classification, presented in Table 1 (country classification available at: https://www.msci.com/our-solutions/index/emerging-markets, accessed on 1 March 2024). We used data of the stock markets from G20 countries that offer a more comprehensive assessment of global market efficiency. By increasing the analysis, researchers can gain insights into a broader range of economies and market dynamics, such as inclusion of major emerging economies and diversity of market characteristics. It recognizes the significance of major emerging economies, captures diverse market characteristics, explores interconnectedness and spillover effects, informs policy discussions, and helps investors make informed decisions. By expanding the analysis beyond the developed countries of G7, the results achieved in this paper will contribute to a deeper understanding of global market dynamics and promote more effective policymaking and investment strategies. The analysis makes use of the closing index price data (until 9 May 2022), while the starting date of each index's data varies depending upon the availability of the data. The stock index data were obtained from www.finance.yahoo.com and www.investing.com.

Table 1. List of G20 countries with the individual stock index, split by market classification considered in this paper.

S. No.	Country	Stock Index	MSCI Classification	Starting Date	Observations
1	Brazil	IBOVESPA	Emerging Markets	5 January 1998	6019
2	France	CAC 40	Developed Markets	5 January 1998	6213
3	Germany	DAX PERFORMANCE-INDEX	Developed Markets	5 January 1988	8677
4	Canada	S&P/TSX Composite index	Developed Markets	5 January 1988	8638
5	Indonesia	Jakarta Composite Index	Emerging Markets	4 January 1994	6912
6	South Korea	KOSPI	Emerging Markets	6 January 1998	6003
7	Argentina	MERVAL	Emerging Markets	2 January 1998	5954
8	Mexico	IPC MEXICO	Emerging Markets	4 January 1994	7107
9	Japan	Nikkei 225	Developed Markets	6 January 1981	10,166
10	China	SSE Composite Index	Emerging Markets	3 July 1997	6016
11	Turkey	BIST 100	Emerging Markets	3 January 2002	6207
12	USA	Dow Jones Industrial Average	Developed Markets	7 December 1999	5644
13	Italy	FTSE MIB	Developed Markets	14 January 2003	4846
14	UK	FTSE 100	Developed Markets	4 January 2001	5395
15	Russia	MOEX	Emerging Markets	10 March 2009	2248
16	South Africa	JSE Top 40	Emerging Markets	3 January 2007	5592
17	India	S&P BSE Sensex	Emerging Markets	4 January 2000	5535
18	Australia	S&P/ASX 200	Developed Markets	5 January 2000	5654
19	Saudi Arabia	TASI	Emerging Markets	15 January 2000	5879

To examine stock market efficiencies and to reveal the inner dynamics of G20 countries, we performed distant analysis of the emergence of the global COVID-19 pandemic and Russia–Ukraine War. Previous studies show that complex systems like stock markets disclose a better structure under stress (Sornette 2003). Therefore, two sub-sample periods were created separately; to examine the impact of the global pandemic, the data were portioned based on the first reported COVID-19 case, and for the Russia–Ukraine War, we chose 24 February 2022 (the day Russia launched a military invasion of Ukraine) as the starting point, as shown in Table 2.

Table 2. The sub-sample division of G20 stock markets during the crisis events of COVID-19 and Russia–Ukraine War.

S. No.	Country	COVID-19		Russia–Ukraine War
		Observations	**1st Case**	**Observations**
1	Brazil	489	27 February 2020	49
2	France	537	24 January 2020	50
3	Germany	530	27 January 2020	50
4	Canada	518	26 January 2020	52
5	Indonesia	484	2 March 2020	43
6	South Korea	516	22 January 2020	50
7	Argentina	482	3 March2020	48
8	Mexico	502	28 February 2020	50
9	Japan	510	22 January 2020	48
10	China	519	31 December 2019	48
11	Turkey	486	11 March 2020	48
12	USA	524	22 January 2020	52
13	Italy	527	31 January 2020	50
14	UK	524	31 January 2020	48
15	Russia	519	31 January 2020	33
16	South Africa	495	5 March 2020	48
17	India	516	30 January 2020	48
18	Australia	528	26 January 2020	50
19	Saudi Arabia	493	2 March 2020	48

2.2. Methodology

This study performs multifractal detrended fluctuation analysis (MFDFA) to analyze the multifractal pattern and to measure the efficiency of the G20 stock market indices during the overall and the sub-sample period of the COVID-19 outbreak. We converted the daily index prices of all the stock markets into index returns, where $P_i(t)$ is the closing price of index i on the business day t, and log returns for the index after the interval Δt can be calculated as:

$$r_i(t) = ln\ P_i(t) - lnP_i(t - \Delta t)$$

The process of MFDFA as mentioned by Kantelhardt et al. (2002) is summarized as follows:

Let $\mathrm{X_t}(\mathrm{t} = 1, 2, \ldots, \mathrm{N})$ signify a time series of finite length N having an insignificant fraction of zero values. In a condition where the series includes zero values, for example, $\mathrm{X_t} = 0$, this can be considered as having no value at the period t. The corresponding profile is determined by integration as follows (Chattopadhyay et al. 2018):

$$\mathrm{Y(i)} = \sum_{\mathrm{t}=1}^{\mathrm{i}} [\mathrm{X(t)} - \langle \mathrm{X} \rangle], \mathrm{i} = 1, 2, \ldots, \mathrm{N},$$

In the above equation, $\langle \mathrm{X} \rangle$ represents average value of $\mathrm{X_i}$. Following the creation of corresponding profile $\mathrm{Y(i)}$, it is divided into $\mathrm{N_s} = \mathrm{int(N/s)}$ non-overlapping boxes of equal size s. In addition, the least-square fit is applied to the individual segment to obtain local trends. However, the record length N of the time series does not necessarily indicate multiplication of the considered segment s, and a short part of the profile $\mathrm{Y(i)}$ might exist in majority of cases. To overcome this issue, a similar process is repeated beginning from the other end of the profile and therefore resulting in $2\mathrm{N_s}$ segments (Bao et al. 2016). Further, the local trend $\mathrm{y}_\upsilon(\mathrm{i})$ against every window $\upsilon = 1, 2, \ldots, 2\mathrm{N_s}$ is achieved by the least square fit, and then the variance is calculated based on the following:

$$\mathrm{F^2(S, \upsilon)} = \frac{1}{\mathrm{S}} \sum_{\mathrm{i}=1}^{\mathrm{S}} \{\mathrm{Y}[(\upsilon - 1)\mathrm{S} + \mathrm{i}] - \mathrm{y}_\upsilon(\mathrm{i})\}^2$$

for $\upsilon = 1, 2, \ldots, N_s$ and using

$$F^2(S, \upsilon) = \frac{1}{S}\sum_{i=1}^{S}\{Y[N - (\upsilon - N_s)S + i] - y_\upsilon(i)\}^2$$

for $\upsilon = N_s + 1, \ldots, 2N_s$. Here, $Y_\upsilon(i)$ is the polynomial fit in box υ. Since the detrending of the time series is performed through deduction of the fits from the profile, different-order MFDFA differs in its capability of eliminating trends in the series. In the mth order of MFDFA, trends of order m in the profile along with $m - 1$ in the original record are disregarded. Therefore, linear (MFDFA1), quadratic (MFDFA2), cubic (MFDFA3), or greater order polynomials can be examined in the fitting process (San José Martínez et al. 2021). Moreover, a comparison of the results for various orders of MFDFA permits approximation of the polynomial trends in the data.

The qth-order fluctuation function is obtained by averaging over all the segments.

$$F_q(S) = \left\{\frac{1}{2N_S}\sum_{\upsilon=1}^{2N_S}\left[F^2(S, \upsilon)\right]^{\frac{q}{2}}\right\}^{\frac{1}{q}}$$

The index variable q can take any real non-zero value. For $q = 0$, the fluctuation function can be obtained using the following:

$$F_0(S) = \exp\left\{\frac{1}{4N_S}\sum_{\upsilon=1}^{2N_S}\ln\left[F^2(S, \upsilon)\right]\right\}$$

For $q = 2$, the standard DFA procedure is obtained. Finally, the scaling behavior of the fluctuation function is determined by considering the log–log graphs of $F_q(S)$ versus S for that particular q. A power law dependence of $F_q(S)$ on the segment size S is given as follows, which signals the availability of scaling behavior:

$$F_q(S) \sim S^{h(q)}$$

The exponent h_q is denoted as a generalized Hurst index, and $h(2)$ is the well-known Hurst exponent H (Zhang et al. 2008). Normally, if $h(q)$ is independent of q, which means $\Delta h(q) = h(q_{min}) - h(q_{max}) = 0$, the time series is monofractal, and if $h(q)$ depends on q, the correlation is multifractal (Zhang et al. 2019a). Numerous studies used $\Delta h(q)$, known as the degree of multifractality, to measure market efficiency (Zunino et al. 2009; Kristoufek and Vosvrda 2013; Miloş et al. 2020). For positive values of q, $h(q)$ explains the scaling behavior of segments with greater fluctuations, while for negative values of q, $h(q)$ shows the scaling behavior of segments with lower fluctuations (Zhang et al. 2019b). If $h(2) > 0.5$, these types of fluctuations towards q are persistent, highlighting an increase (decrease) is likely to be followed by another increase (decrease). However, if $h(2) < 0.5$, this represents fluctuations towards q being anti-persistent, which implies that an increase (decrease) is likely to be followed by another decrease (increase). Moreover, in a condition where $h(2) = 0.5$, this shows types of fluctuations depicting a random walk behavior.

Further, we obtained the Renyi exponent $\tau(q)$, which can be utilized to specify the multifractal properties (Shadkhoo and Jafari 2009). This relationship among $\tau(q)$ and that of the generalized Hurst exponent $h(q)$ can be achieved by the following:

$$\tau(q) = qh(q) - 1$$

If the association between $\tau(q)$ and q is linear, the cross-correlation among the two series is considered monofractal. If the scaling exponent $\tau(q)$ is not linear to q, the cross-correlation between the two sequences is multifractal.

The complexity in a time series can be rightly obtained by the singularity spectrum, $f(\alpha).\alpha$ and $f(\alpha)$ can be formed by a Legendre transform of q and $\tau(q)$.

$$\alpha = \frac{d\tau(q)}{dq}$$

$$f(\alpha) = q\alpha(q) - \tau(q)$$

The curve $f(\alpha)$ is an individual humped function in a multifractal time series that decreases to a point for a monofractal. The multifractal spectrum highlights the significance of numerous fractal exponents in the time series (Zou and Zhang 2019), where ΔH is the width of the multifractal spectrum that is utilized to obtain the intensity of the multifractality.

$$\Delta H = H_{max}(q) - H_{min}(q)$$

3. Empirical Results and Discussion

This section presents the findings of the MFDFA method conducted on the G20 stock market indices during the overall and sub-sample periods. The analysis and discussion in this section focus on the statistics of the stock index returns followed by a detailed examination of the fractal structures and behavior of G20 stock markets.

3.1. Descriptive Statistics

The descriptive statistics of G20 stock markets in Table 3 show the average, maximum value, minimum value, standard deviation, skewness, and kurtosis of developed and emerging stock markets under overall sample and crisis periods of the COVID-19 outbreak and Russia–Ukraine War. The results show that returns are almost zero for the G20 stock markets, with an average of 0.00015 for the developed and 0.00042 for the emerging stock markets during the overall period. Similarly, the average standard deviation for emerging stock markets is slightly higher at 0.01621 compared with 0.01270 for the developed stock markets. These results prove a key hypothesis of corporate finance, which mentions that higher returns are associated with higher risk (Chari et al. 2019). In addition, all the returns are negatively skewed, except for the emerging stock markets of Brazil and Mexico. The results further show a kurtosis coefficient value of above three during the overall period, representing the fat-tailed behavior of the G20 stock markets.

To assess the changes during the crises, the data set was divided into sub-sets of during the COVID-19 outbreak and during the Russia–Ukraine War. We observed zero mean returns for all the stock markets during COVID-19, with an average of 0.00026 for the developed and 0.00080 for emerging stock markets. Except for Japan and Indonesia, all other stock index returns were negatively skewed during the pandemic period. Moreover, the high kurtosis values show the availability of heavy tails in the G20 stock markets. A consistent small fluctuation in the statistics of returns is observed for all the G20 stock markets specifically during the outbreak. In addition, the period of the Russia–Ukraine War represents negative average stock returns for the developed countries of −0.00089 compared to −0.00006 for the emerging markets. Moreover, positive standard deviation was observed during this period for all the stock returns, except for Brazil.

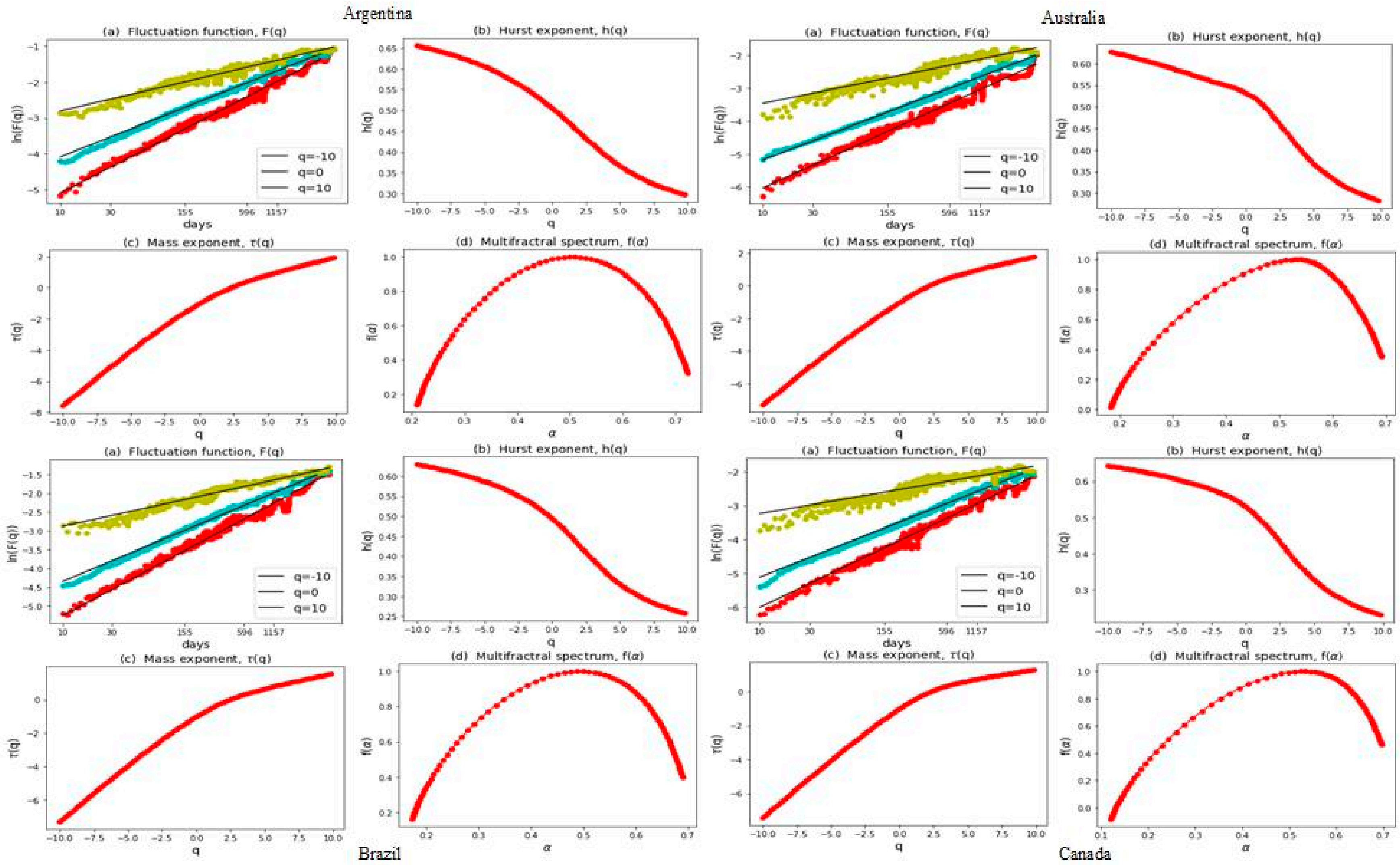
Table 3. Summary statistics of the G20 stock index returns categorized in accordance with MSCI classification during the overall and crisis periods of COVID-19.

	Developed Markets								Emerging Markets										
Statistics	**Australia**	**Canada**	**France**	**Germany**	**Italy**	**Japan**	**UK**	**USA**	**Argentina**	**Brazil**	**China**	**India**	**Indonesia**	**Mexico**	**Russia**	**Saudi Arabia**	**South Africa**	**South Korea**	**Turkey**
Overall Period																			
Mean	0.00016	0.00022	0.00013	0.00033	−0.00001	0.00014	0.00003	0.00020	0.00079	0.00043	0.00019	0.00043	0.00035	0.00044	0.00055	0.00029	0.00026	0.00036	0.00047
Maximum	0.06765	0.11295	0.10595	0.10797	0.10874	0.13235	0.09384	0.10764	0.16117	0.28832	0.09401	0.15990	0.13128	0.12154	0.08527	0.09391	0.09057	0.11284	0.12128
Minimum	−0.10203	−0.13176	−0.13098	−0.14091	−0.18541	−0.16135	−0.11512	−0.13842	−0.47692	−0.17208	−0.09256	−0.14102	−0.12732	−0.14314	−0.11419	−0.10328	−0.10450	−0.12805	−0.13336
Std. Dev.	0.01024	0.00997	0.01437	0.01406	0.01515	0.01387	0.01192	0.01198	0.02367	0.01979	0.01549	0.01465	0.01475	0.01441	0.01412	0.01386	0.01340	0.01657	0.01765
Skewness	−0.72252	−0.99786	−0.20994	−0.30863	−0.71438	−0.31815	−0.33940	−0.38004	−1.67487	0.23511	−0.34561	−0.38001	−0.19365	0.00320	−0.43110	−0.94226	−0.21059	−0.19484	−0.24160
Kurtosis	8.48142	18.95541	5.98165	6.75656	11.06836	8.20312	8.31338	13.13340	32.44721	14.64744	4.99352	9.24214	9.00441	6.95215	6.67578	10.90441	5.50566	5.88648	4.82828
COVID-19 Period																			
Mean	0.00011	0.00037	0.00027	0.00036	0.00017	0.00056	−0.00015	0.00037	0.00187	0.00038	0.00042	0.00069	0.00031	0.00058	0.00058	0.00117	0.00070	0.00108	0.00100
Maximum	0.06765	0.11295	0.08056	0.10414	0.08549	0.07731	0.08667	0.10764	0.09773	0.13022	0.05554	0.08595	0.09704	0.04181	0.07435	0.06831	0.09057	0.08251	0.05810
Minimum	−0.10203	−0.13176	−0.13098	−0.13055	−0.18541	−0.06274	−0.11512	−0.13842	−0.15629	−0.15993	−0.08039	−0.14102	−0.06805	−0.06638	−0.08646	−0.08685	−0.10450	−0.08767	−0.10307
Std. Dev.	0.01646	0.01818	0.01790	0.01832	0.01974	0.01514	0.01647	0.02006	0.03068	0.02607	0.01213	0.01861	0.01563	0.01440	0.01489	0.01307	0.01764	0.01637	0.01609
Skewness	−1.21347	−1.57054	−1.30610	−0.96209	−2.87862	0.10497	−1.09657	−0.93904	−0.81817	−1.58969	−0.87744	−1.62935	0.04899	−0.56564	−0.88221	−2.19058	−0.62578	−0.23797	−1.76801
Kurtosis	8.51725	20.37049	11.41289	11.30552	26.32322	4.26268	10.12222	12.78127	4.54731	12.33200	6.99797	13.50224	6.69740	2.40750	9.21193	16.89974	9.28752	5.54108	9.31730
Russia–Ukraine War																			
Mean	−0.00024	−0.00070	−0.00114	−0.00089	−0.00128	−0.00010	−0.00226	−0.00052	−0.00219	−0.00166	−0.00312	−0.00103	0.00102	−0.00092	0.00334	0.00204	−0.00266	−0.00091	0.00544
Maximum	0.01309	0.01801	0.06883	0.07623	0.06714	0.03860	0.01603	0.02775	0.03961	0.02396	0.03424	0.02407	0.01164	0.02118	0.18262	0.01984	0.04083	0.02185	0.05312
Minimum	−0.03031	−0.03119	−0.04019	−0.04040	−0.04288	−0.02984	−0.03955	−0.03171	−0.05054	−0.02898	−0.05268	−0.04836	−0.01488	−0.02300	−0.05016	−0.01853	−0.03882	−0.02635	−0.08517
Std. Dev.	0.00931	0.01000	0.01898	0.01950	0.01925	0.01540	0.01186	0.01344	0.01862	−0.01295	0.01685	0.01454	0.00636	0.01087	0.04327	0.00754	0.01532	0.01041	0.01708
Skewness	−1.08036	−0.70804	0.90073	1.14621	0.52950	0.29886	−1.24770	−0.32308	−0.18390	−0.13115	−0.72397	−0.51137	−0.43071	0.11286	2.30444	−0.57090	0.08121	−0.14914	−2.69559
Kurtosis	1.24220	0.94405	2.82615	3.99206	2.59417	−0.15874	1.79912	−0.01733	0.55965	−0.42126	1.44283	0.87097	−0.60784	−0.59640	7.82037	0.64723	0.64424	−0.14665	16.79280

3.2. Multifractal Structures of G20 Stock Markets

Figure 1A–E represents the MFDFA results for all G20 markets during the overall period of study. The fluctuation function $F(q)$ shows a well-fitted straight line in log–log scale at $q = -10$, $q = 0$, and $q = 10$. The slopes of fitted lines correspond to the generalized Hurst exponent, which is calculated by defining $q = 2$ for the scaling exponent, for the stationary time series. The Hurst exponent in Figure 1A(b) represents the dependence of the generalized Hurst exponent with q. While considering the case of the Argentina stock market, the slopes of fitted lines related to the generalized Hurst exponent certainly rely on q (i.e., $h(-10) = 0.772$, $h(0) = 0.608$, $h(10) = 0.330$). The q-dependency for the scaling exponent indicates the multifractal structures of the Argentina stock market. This declining trend, where the slope of negative q becomes steeper, compared with the positive values of q, matches with the theoretical property of the generalized Hurst exponent (Diniz-Maganini et al. 2021). Figure 1A(c) displays the Renyi exponent, $\tau(q)$, which clearly shows an exponential shape representing the multifractal series. Figure 1A(d) displays the multifractal spectrum $f(\alpha)$, represented by a single humped shape, verifying the presence of multifractality in the MERVAL stock index. In addition, the supplementary file includes all the figures of the results during the overall and sub-sample crisis periods. Further, we obtained the same results and structures from all the remaining G20 stock markets. Moreover, the range of multifractality degree Δh obtains the level of multifractality, with higher values corresponding to higher multifractality in the return series (Kantelhardt et al. 2002). In our case, the width of the generalized Hurst exponent Δh for the Argentina stock market is noted to be 0.442.

Table 4 presents a summary of all the G20 stock markets for the overall period and categorized in accordance with the MSCI classification for the developed and emerging stock markets with the range of $q\epsilon[-10, 10]$. We immediately observed a declining pattern of the $h(q)$ for all the G20 stock markets during the overall period of study. This signifies the availability of multifractality in the overall return series of the G20 stock markets during the entire period of study. In addition, the highest range of the Hurst exponent $(\Delta h = 0.528)$ was noted for the Italian stock market, thus representing the highest level of multifractality, whereas the narrowest ranges of the Hurst exponent were observed for Germany ($\Delta h = 0.210$), and India ($\Delta h = 0.281$), showing the lowest degree of multifractality. The degree of long-range correlations is connected with the multifractal properties, as mentioned in a previous work by Anagnostidis et al. (2016). Therefore, the markets of Germany from the developed markets and India from the emerging markets are displaying the lowest range of dependence.



(**A**)

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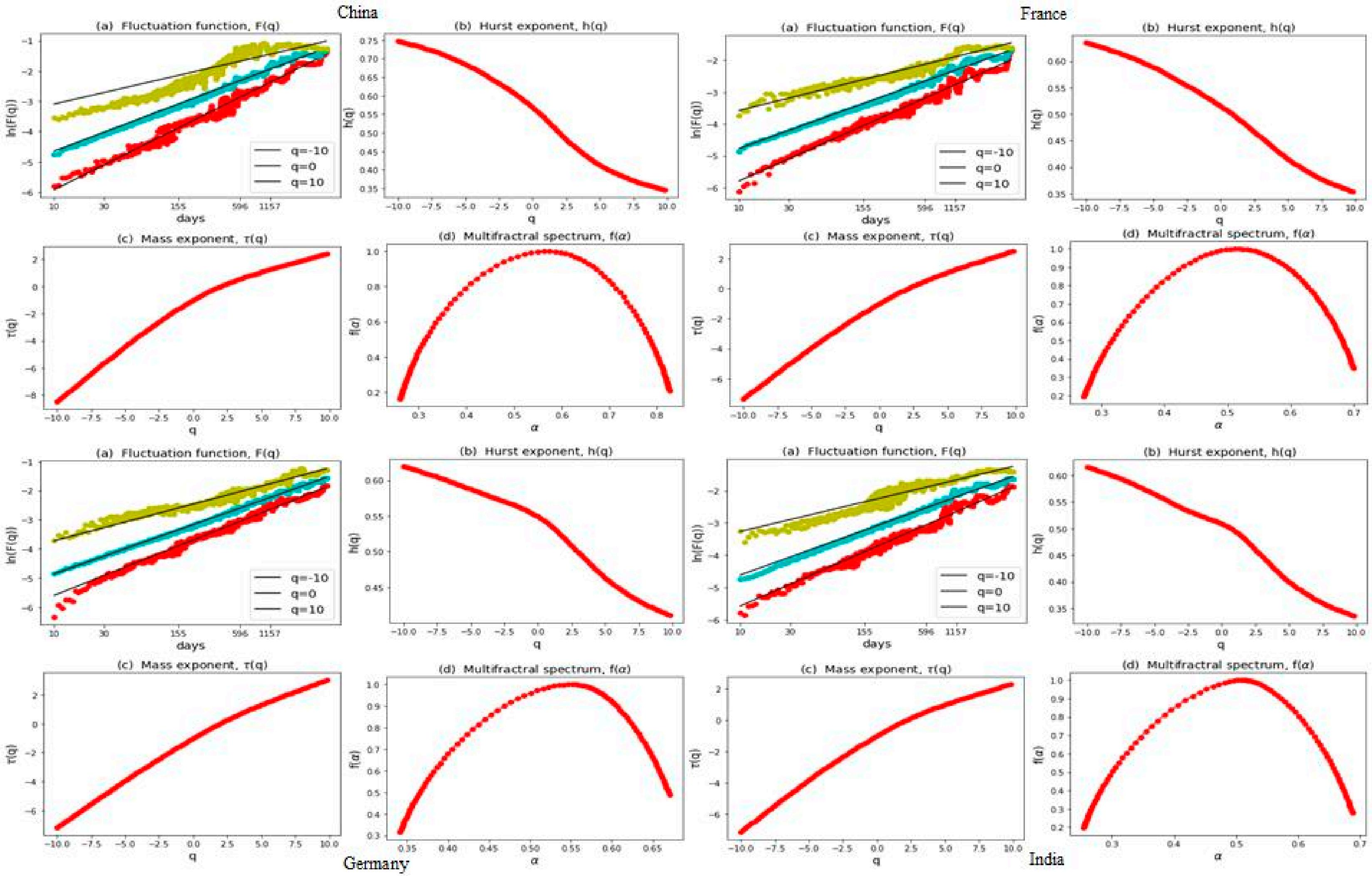

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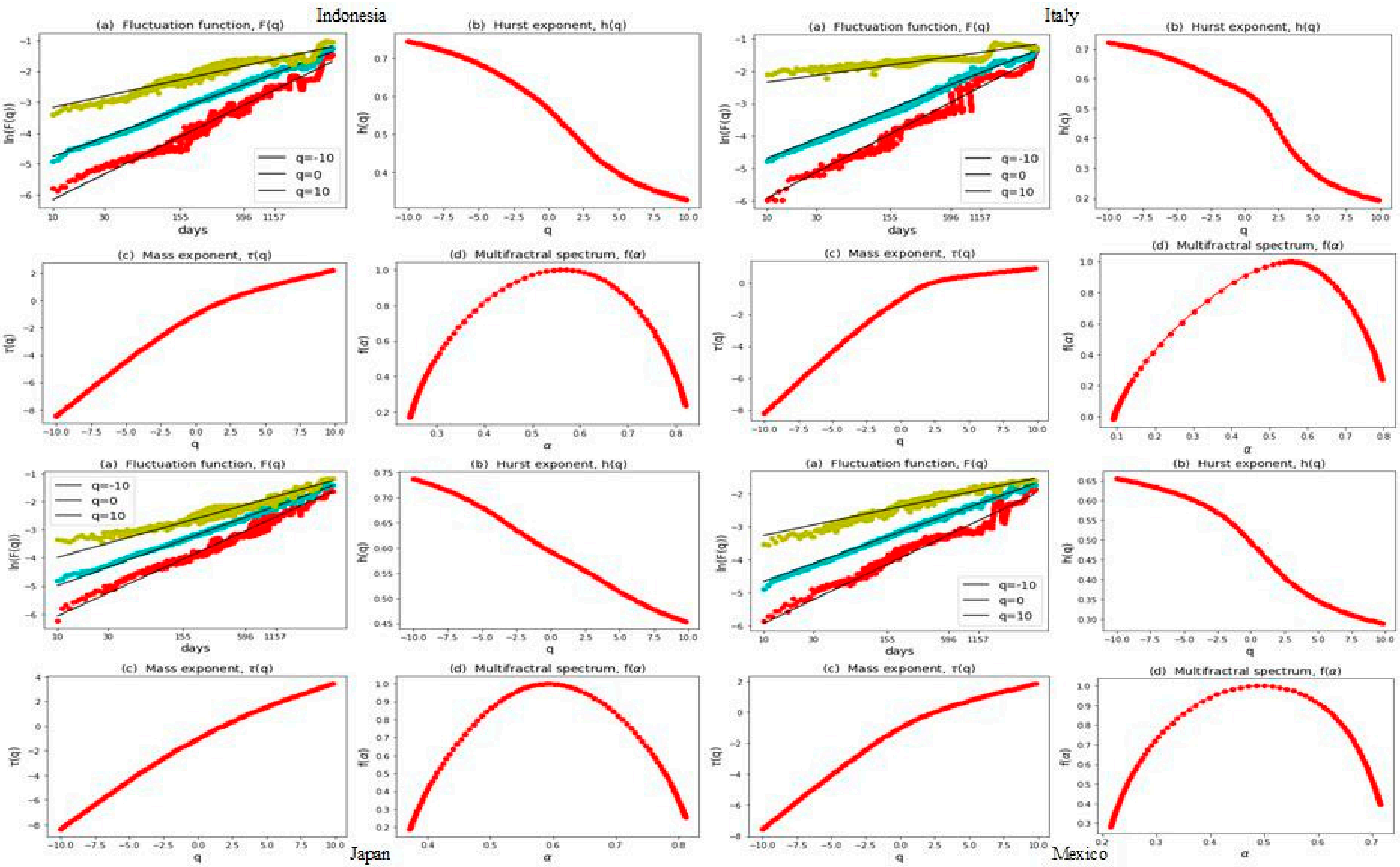

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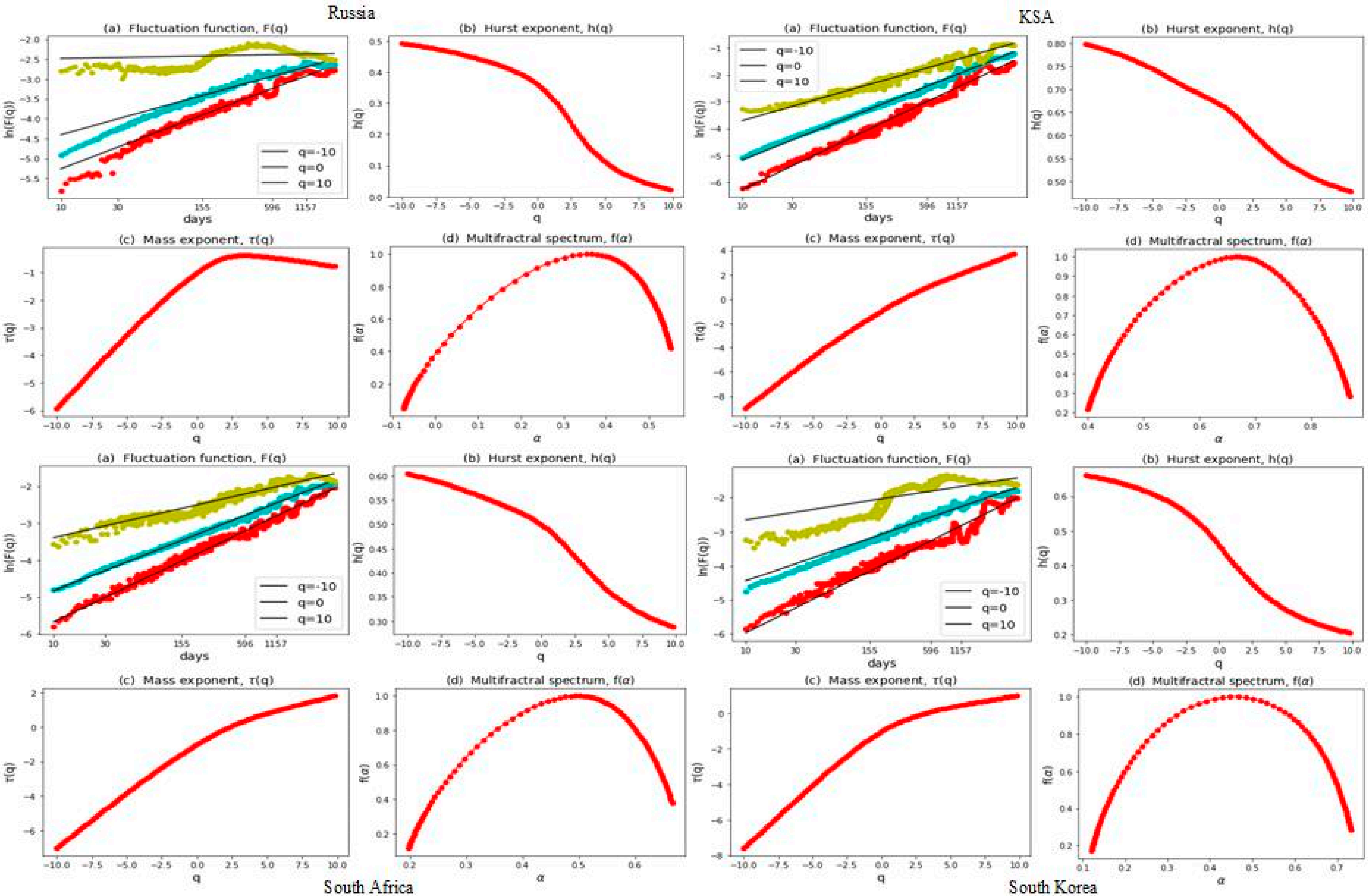

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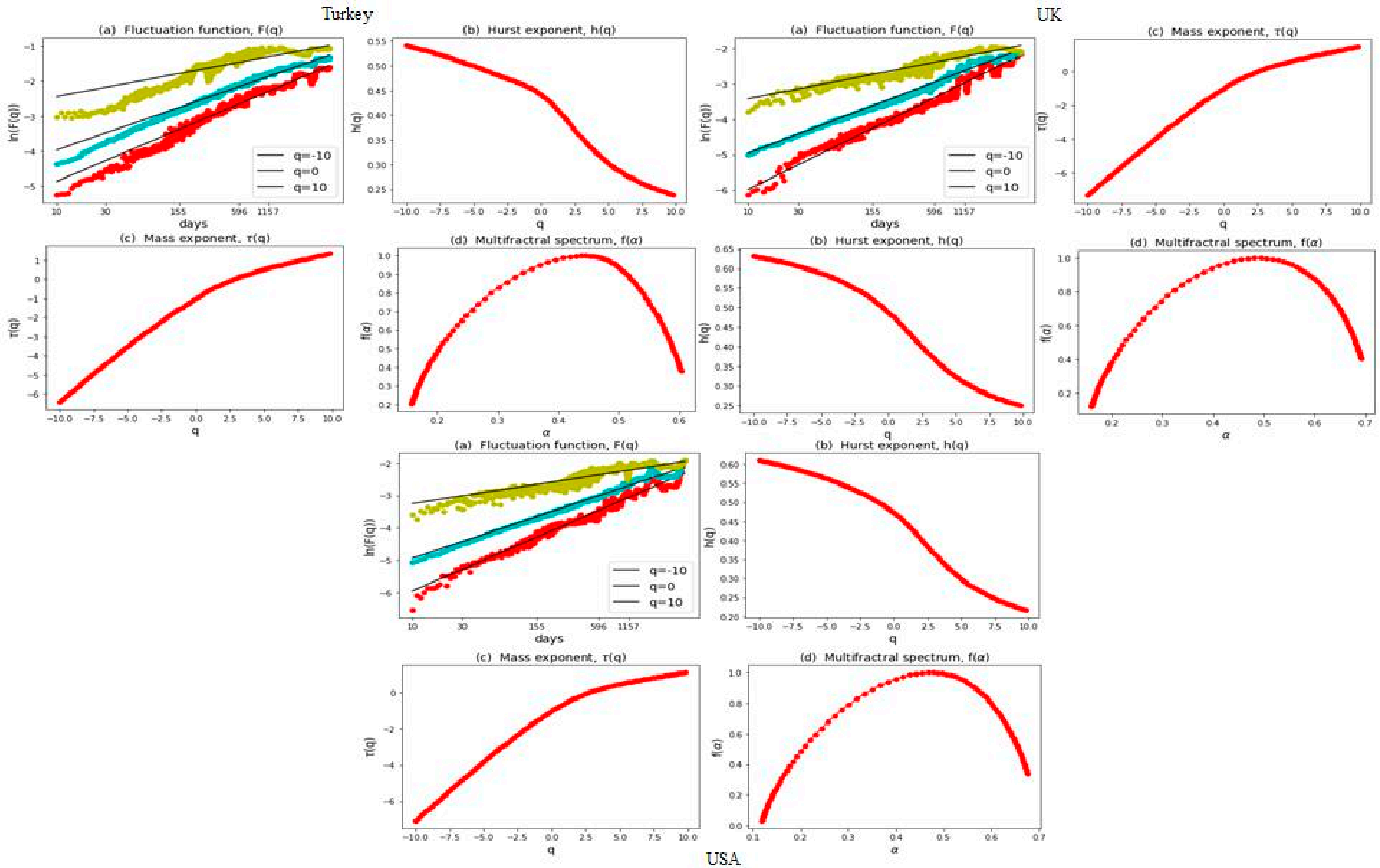


(**E**)

Figure 1. (**A**) The overall period's MFDFA results (Argentina, Australia, Brazil, Canada) of the daily index return time series including, (**a**) fluctuation functions q = −10 (light green), q = 0 (light blue), q = 10 (red), (**b**) generalized Hurst exponent q, (**c**) mass exponent $\tau(q)$, and (**d**) multifractal spectrum $f(\alpha)$. (**B**) The MFDFA results of daily index return time series (China, France, Germany, India) for overall period. (**C**) The MFDFA results of daily index return time series (Indonesia, Italy, Japan, Mexico) for overall period. (**D**) The MFDFA results of daily index return time series (Russia, Saudi Arabia, South Africa, South Korea) for overall period. (**E**) The MFDFA results of daily index return time series (Turkey, UK, USA) for overall period.

While comparing the developed and emerging stock markets, the average width of the Hurst exponent remained high for the emerging stock markets ($\Delta h = 0.5303$), compared with the developed stock markets' average width of ($\Delta h = 0.5260$). This result is in line with the evidence from Ali et al. (2018) that shows higher market efficiency for the developed stock markets. However, financial liberalization policy initiatives combined with higher capital flows are observed for the emerging stock markets compared with developed stock markets (Cajueiro et al. 2009; Yang et al. 2019). Moreover, France and Germany remain the most efficient developed stock markets with the lowest degrees of multifractality, carrying Hurst exponents of $\Delta h = 0.282$ and $\Delta h = 0.210$, respectively. Meanwhile, from the developed stock markets, the UK and USA remain in the middle with scores of $\Delta h = 0.383$ and $\Delta h = 0.394$, respectively. While comparing all the G20 countries, the results show Germany and India to be the most efficient stock markets among all G20 countries, and Italy remains the least efficient stock market. While examining east Asian stock markets, Rizvi and Arshad (2014) also show the South Korean stock market as dominating with highest efficiency level during both short and long terms. However, the results indicate better efficiency for the China stock market compared with the South Korean stock market. Furthermore, the results should be considered with caution, due to the large sample period of the G20 stock market indices and the variations in the liquidity and volatility of these stock markets that might impact the stock market efficiency (Alam et al. 2016). Our results agree with Figliola et al. (2010) and Wang and Liu (2020), who mention the multifractal structures of stock markets. In addition, the results of our study corroborate with Arshad et al. (2016) and Rizvi and Arshad (2017) regarding the efficiency of stock markets.

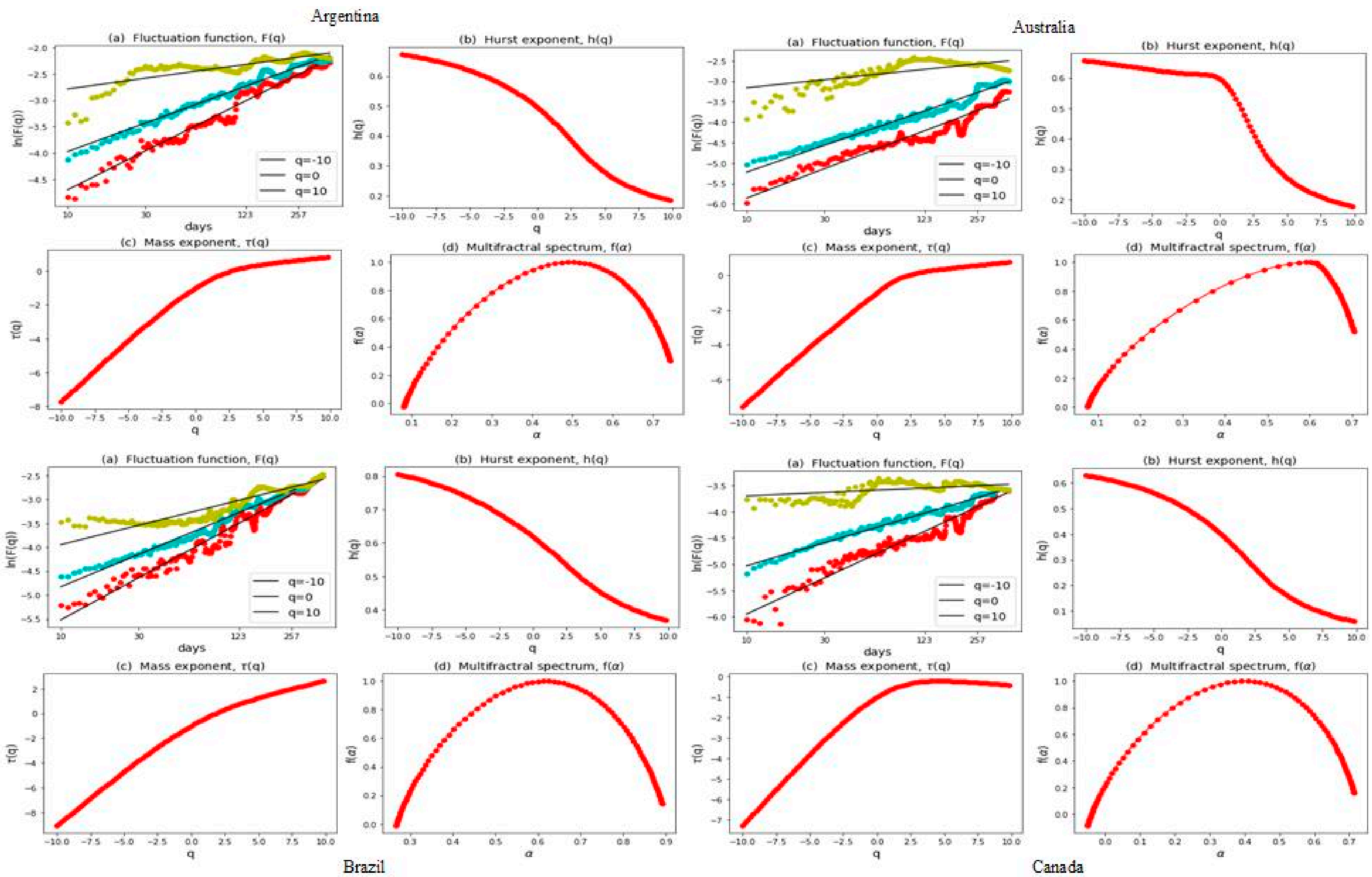
The COVID-19 crisis period's MFDFA results for all G20 markets are presented in Figures 2 and 3A–E. Similarly, all the figures exhibit the remaining figures [i.e., fluctuation function $F(q)$, Hurst exponent $h(q)$, Renyi exponent $\tau(q)$, and multifractal spectrum $f(\alpha)$] of all G20 stock markets during the sub-sample crisis periods of the COVID-19 pandemic and the Russia–Ukraine War. The results show a declining pattern of $h(q)$ for all the G20 stock markets (Table 5), confirming the multifractality of G20 stock markets during both of the crisis periods as well. In addition, we immediately observed a tremendous increase in the width of generalized Hurst exponent Δh for almost all the G20 stock markets, except Italy and China. This shows a high level of unevenness in the local fluctuations of G20 stock markets, considering the sheer magnitude and impact of COVID-19 on the world stock markets (Aslam et al. 2020d). As crises often involve a high degree of complexity and uncertainty, the irregular pattern becomes visible and is shown by other similar studies, in particular for the crisis caused by the COVID-19 pandemic (Aslam et al. 2020c; Saâdaoui 2023). Furthermore, the crisis period of the Russia–Ukraine War presents an interesting finding of the highest width of generalized Hurst exponent for the two developed stock markets of Canada and the UK and for the six emerging stock markets of Argentina, China, India, Russia, Saudi Arabia, and South Africa. The decline in the efficiency of G20 stock markets is evident due to uncertainty and discouraging investment by the investors in these stock markets during these crisis events (Salisu and Vo 2020). More specifically, the least efficient G20 stock markets during the global pandemic with the highest multifractality are Russia, with a width of generalized Hurst exponent of $\Delta h = 0.7394$, followed by South Korea, which demonstrated a higher range of generalized Hurst. Similarly, the width of the generalized Hurst exponent further increased to $\Delta h = 0.8659$ for the Russian stock market during the crisis period of the Russia–Ukraine War, thus nominating the Russian stock market as the least efficient stock market among the stock markets of all the G20 countries. The growth of the Hurst exponent for the Russian stock market suggests a high degree of long-range dependence in the stock price. According to Derindere Köseoğlu et al. (2024), the Moscow exchange index went down following the start of the conflict and reached the bottom level in point-wise causal effect. Moreover, the impact of the Russia–Ukraine conflict was significant and affected the Russian stock market directly, along with various sectors and assets (Izzeldin et al. 2023). The results further reveal the Chinese stock market to be more efficient with $\Delta h = 0.1923$ during the COVID-19 pandemic, while the stock market of Mexico remains the most efficient with $\Delta h = 0.2066$ during the crisis period of the Russia–Ukraine War. Being the first affected country, it is interesting to note that the Chinese stock market was not impacted much during the pandemic. Particularly, the uncertainty lasted for a shorter period, and impacted few sectors (Wu et al. 2021; Lee et al. 2021), but overall the Chinese stock market remained stable and less sensitive to the COVID-19 shock (He et al. 2020; Gao et al. 2021).

In addition, the average width of the generalized Hurst exponent is lower for the developed markets at $\Delta h = 0.5264$, compared with a higher average width of $\Delta h = 0.5833$ for the emerging markets during the COVID-19 period. Furthermore, the period of the Russia–Ukraine crisis shows a lower width of emerging stock markets of $\Delta h = 0.5607$, compared with a slightly higher width of $\Delta h = 0.5635$ for the developed stock markets. Previous studies mention that stock markets from developed countries performed better during the outbreak due to timely government responses that significantly reduced the impact of the outbreak, compared with emerging stock markets (Salisu et al. 2020). This aligns with our results on the efficiency of the developed stock markets that were comparatively better than the emerging stock markets.

3.3. Range of Persistance and Herding Behavior in the G20 Markets

Previous studies suggest that the Hurst exponent is an authentic measurement for examining the persistence level and herding behavior in a time series (Fernández-Martínez et al. 2017; Mnif et al. 2020; Memon et al. 2022). For the overall period, the results of the Hurst exponent at $q = 2$ (Table 4) nominate the six developed stock markets of the USA $(h(q) = 0.404)$, Australia $(h(q) = 0.479)$, Canada $(h(q) = 0.455)$, France $(h(q) = 0.477)$, Italy $(h(q) = 0.464)$, and the UK $(h(q) = 0.418)$ to be negatively autocorrelated, representing an anti-persistent behavior with no trace of herding. The result can be explained as any change increase (decrease) in the former time period probably being followed by an inverse decrease (increase) in the time period afterwards. Meanwhile, the remaining two developed stock markets, i.e., Germany $(h(q) = 0.518)$ and Japan $(h(q) = 0.562)$, show persistent evidence of moderate herding behavior. This can be interpreted as an increase (decrease) in the former time periods most likely being followed by an increase (decrease) in the later periods. From emerging stock markets, only the two stock markets of Argentina $(h(q) = 0.0.535)$ and Saudi Arabia $(h(q) = 0.620)$ show persistent behavior (positive autocorrelation). However, the rest of the nine emerging stock markets (such as Brazil, China, India, Indonesia, Mexico, Russia, South Africa, South Korea, and Turkey) represent negative autocorrelation with an absence of herding behavior and a bubble. While analyzing numerous emerging and developed markets, Di Matteo et al. (2003, 2005) demonstrated $H > 0.5$ for the emerging and $H < 0.5$ for the well-developed markets. However, based on our results, the developed stock markets obtained an overall average score of $(h(q) = 0.472)$ at $q = 2$, compared with the emerging stock market average of $(h(q) = 0.448)$.

The crisis periods' results further reveal persistence behavior $(H > 0.5)$, i.e., positive autocorrelation for two stock markets including Brazil and South Korea during the COVID-19 period, compared to the seven stock markets of Australia, Japan, UK, Brazil, India, Mexico, and Russia during the Russia–Ukraine War. These results confirm the evidence of the persistence and herding behavior of many stock markets during the crisis time of the Russia–Ukraine War. Moreover, the average Hurst exponent at $q = 2$ during the COVID-19 period for developed stock markets remains at $(h(q) = 0.3640)$, compared with an average of $(h(q) = 0.4390)$ for the emerging stock markets. Meanwhile, the later period shows an average Hurst exponent value of $(h(q) = 0.4721)$ for the developed stock markets, compared to $(h(q) = 0.4437)$ for the emerging markets. The classical Hurst exponent $q = 2$ represents a change in the persistence behavior of G20 stock markets. To sum up, the crisis periods resulted in richer structures for the G20 stock markets that altered their efficiency and exhibited long-range correlations, along with the detection of herding during the later period of the Russia–Ukraine War.



(**A**)

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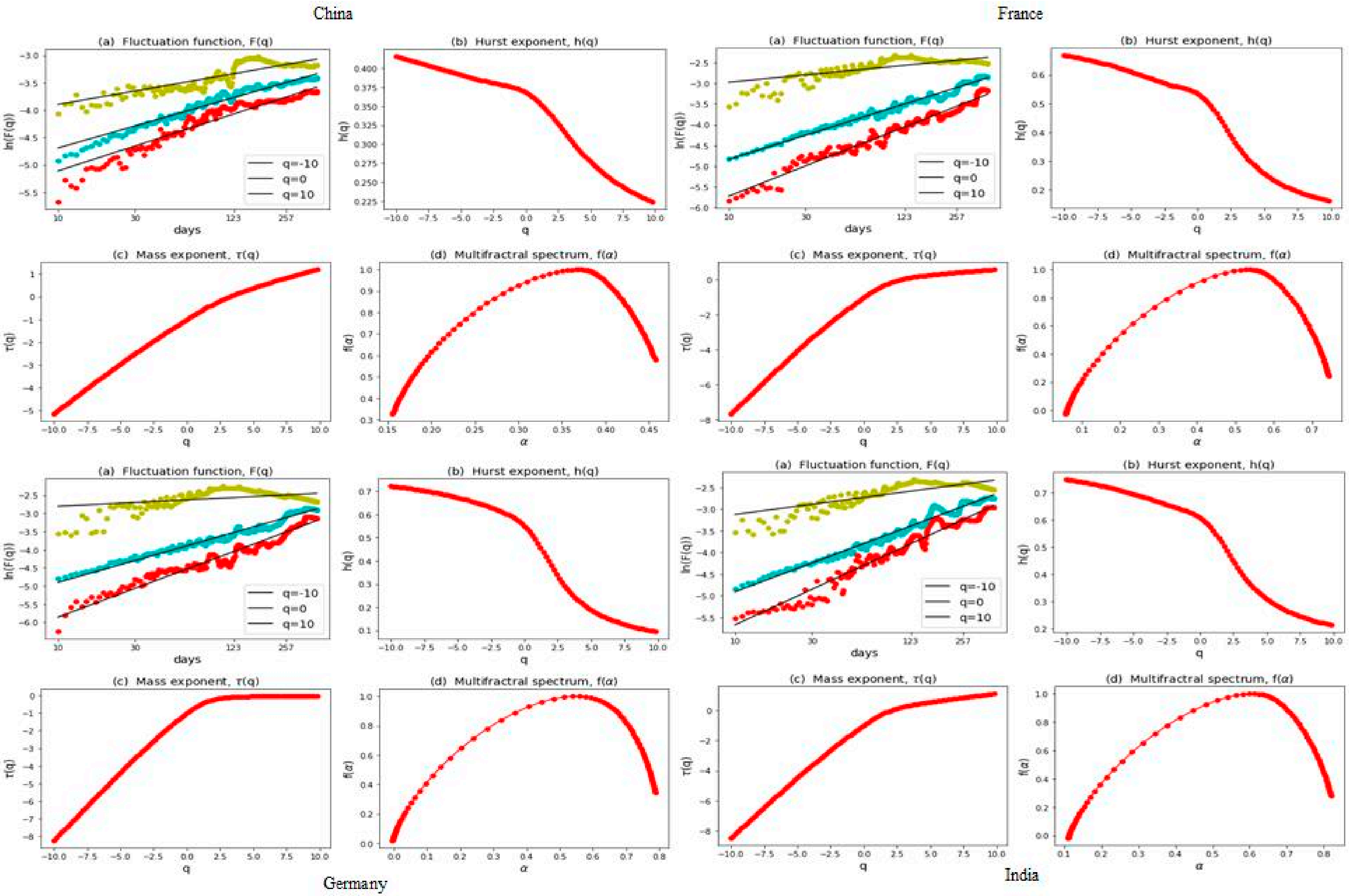

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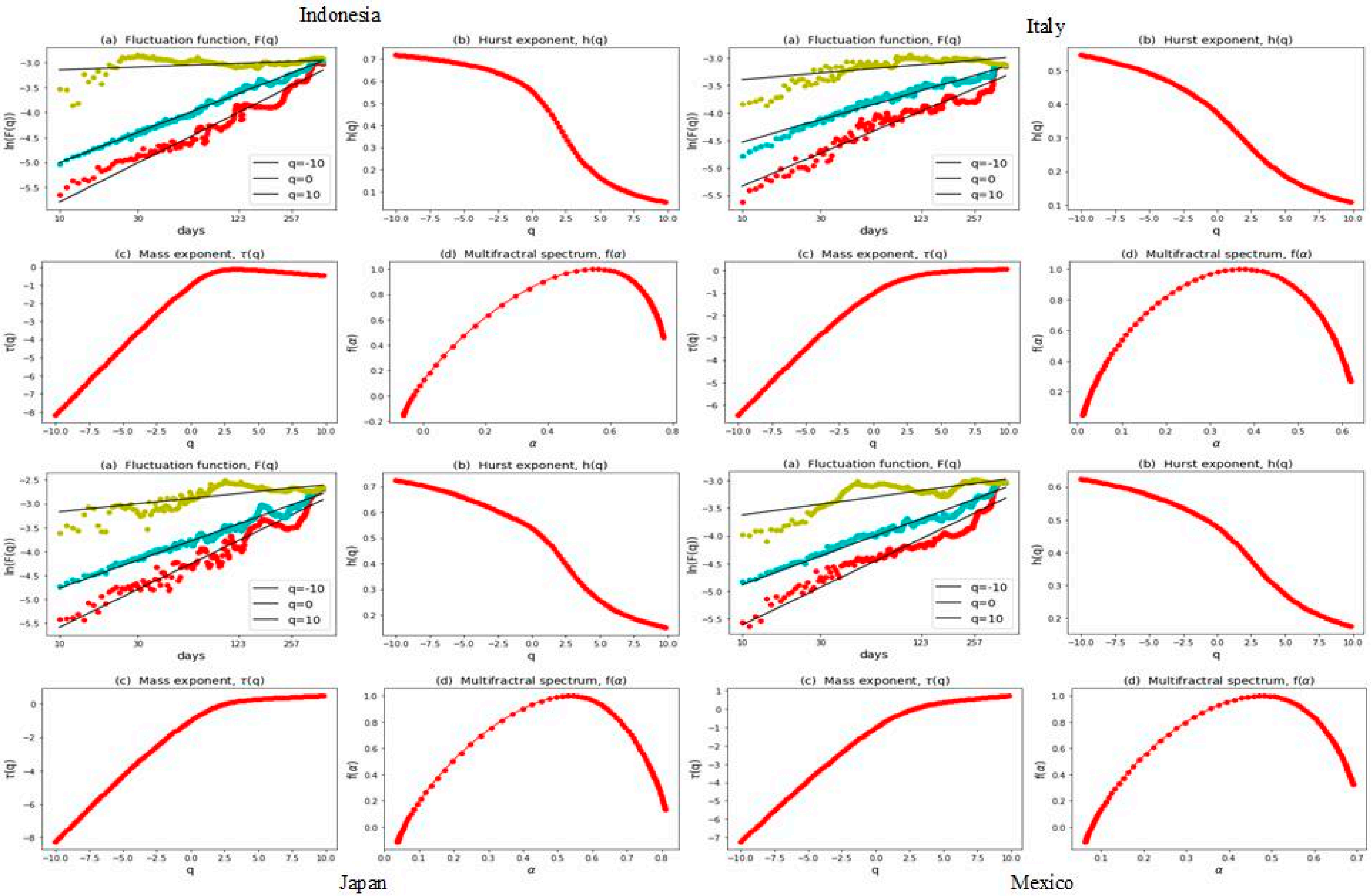

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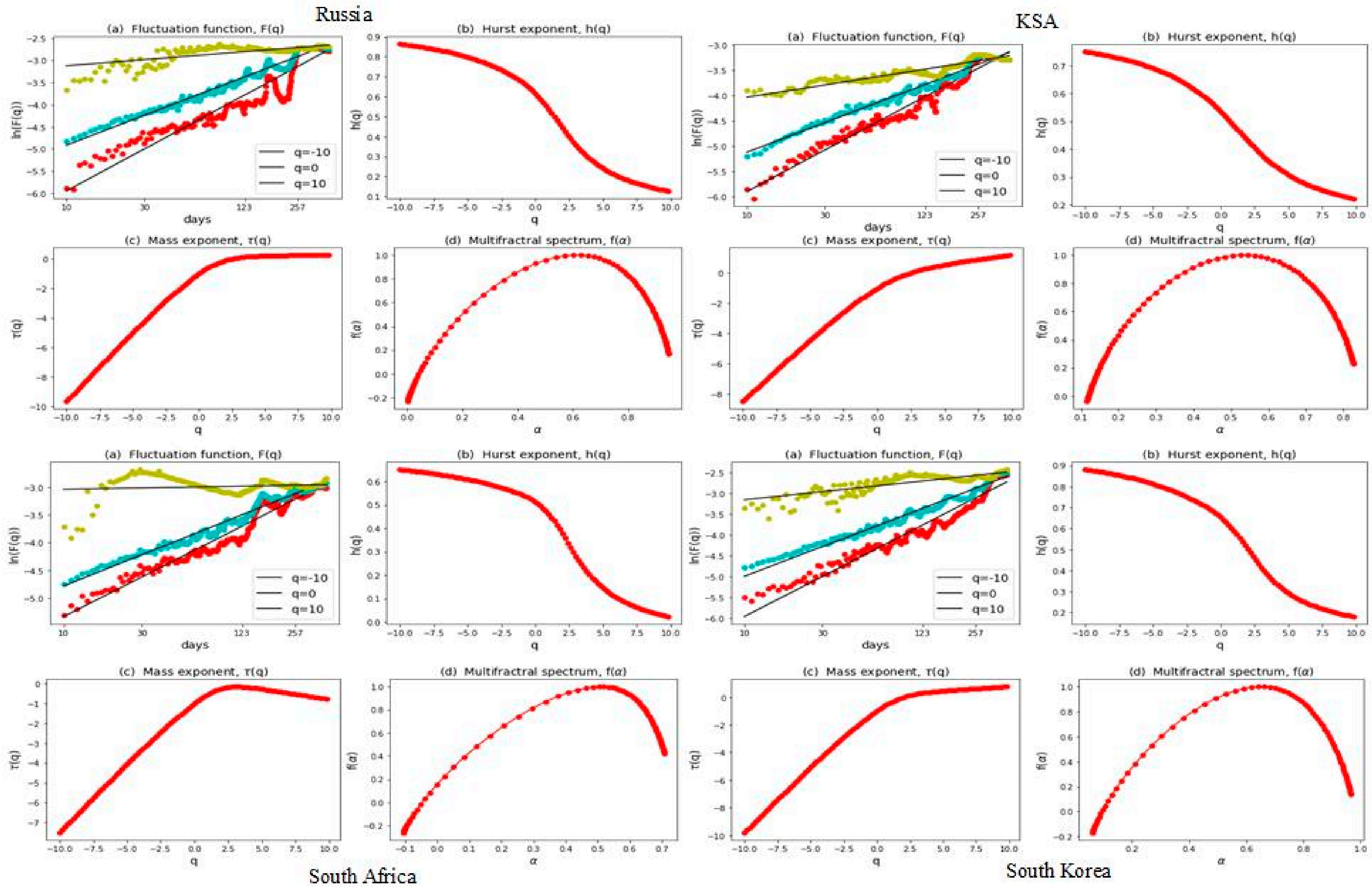

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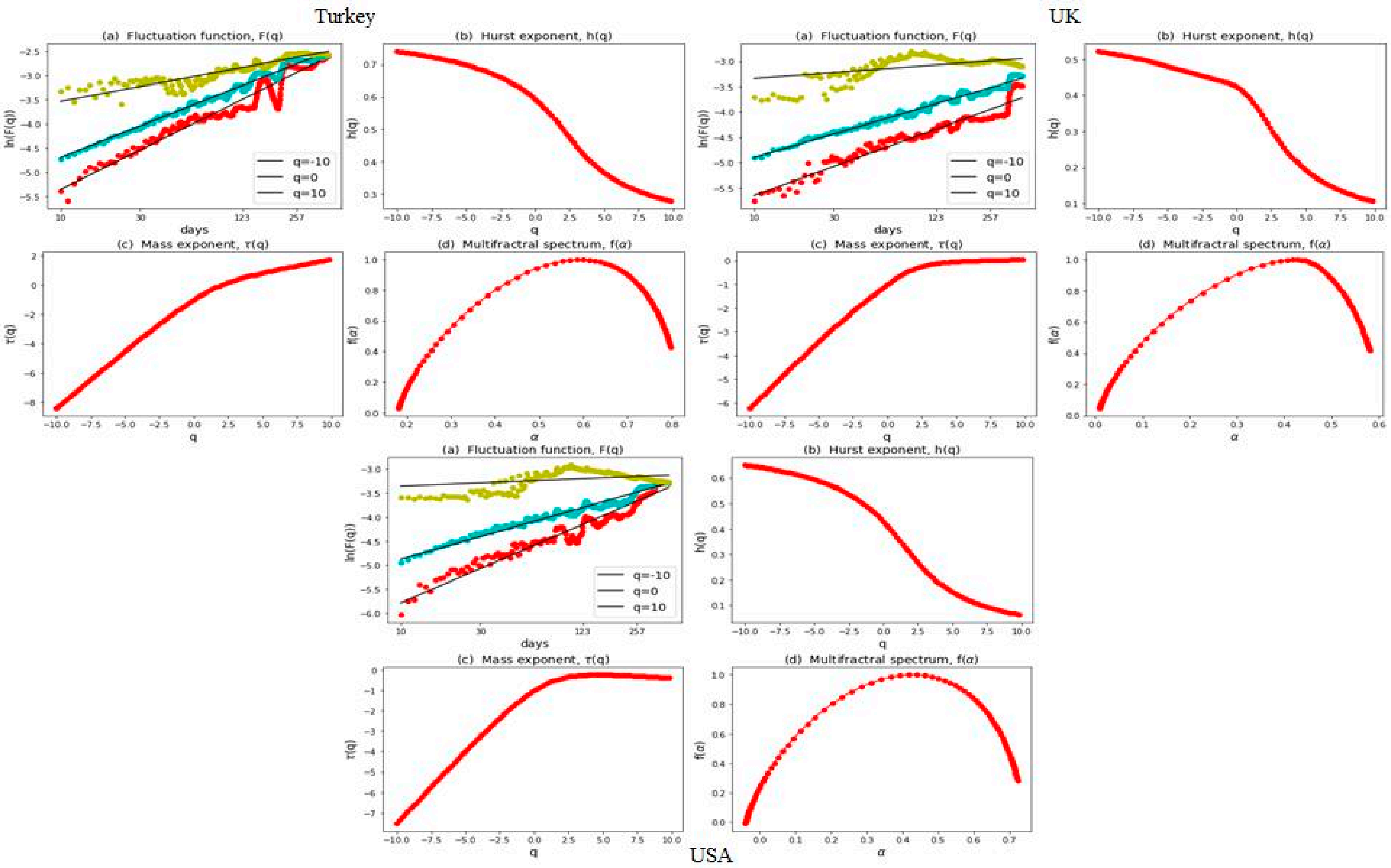
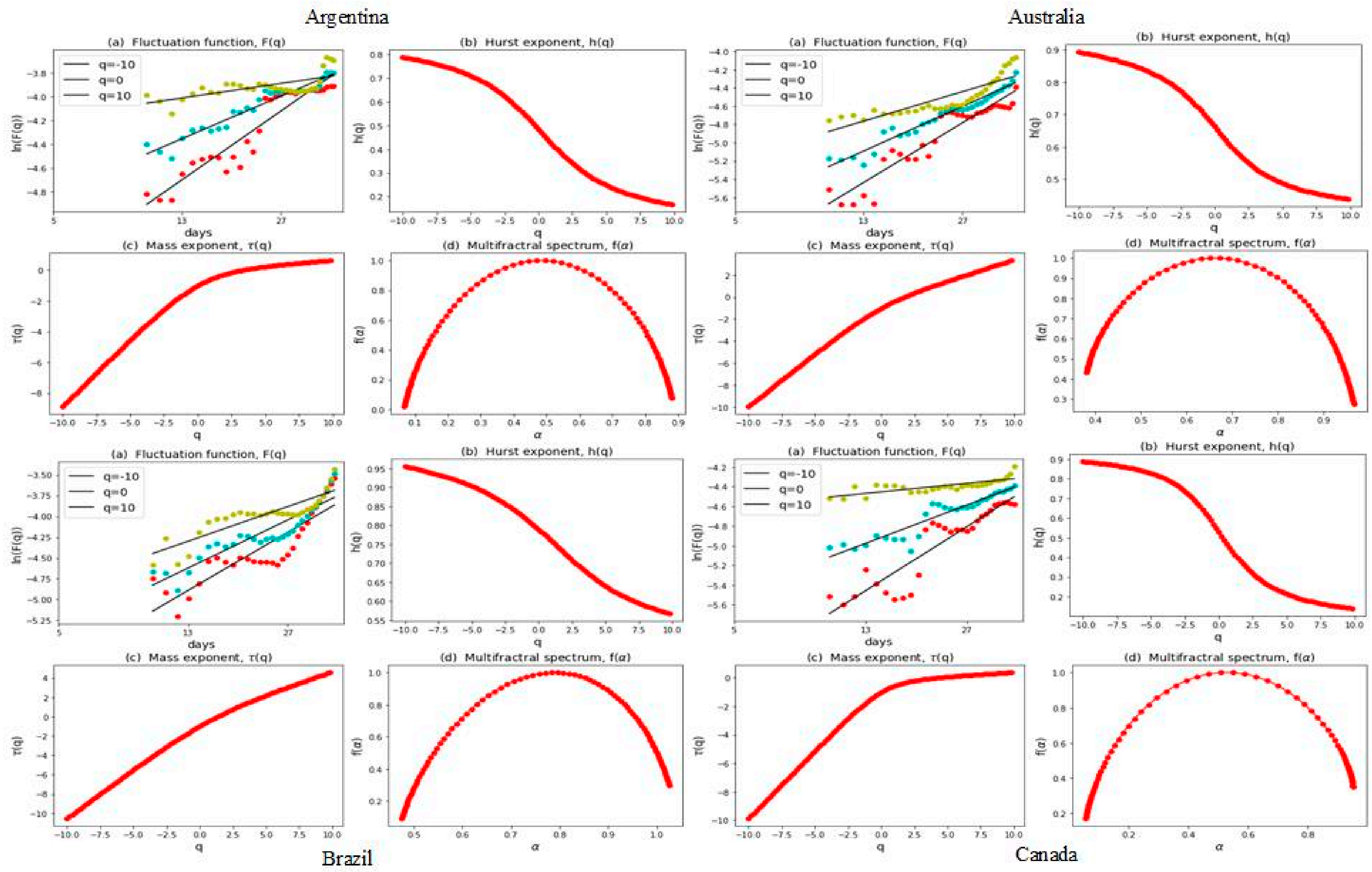


(**E**)

Figure 2. (**A**) The COVID-19 pandemic period's MFDFA results (Argentina, Australia, Brazil, Canada) of the daily index return time series including, (**a**) fluctuation functions q = −10 (light green), q = 0 (light blue), q = 10 (red), (**b**) generalized Hurst exponent q, (**c**) mass exponent $\tau(q)$, and (**d**) multifractal spectrum $f(\alpha)$. (**B**) The MFDFA results of daily index return time series (China, France, Germany, India) during COVID-19 period. (**C**) The MFDFA results of daily index return time series (Indonesia, Italy, Japan, Mexico) during COVID-19 period. (**D**) The MFDFA results of daily index return time series (Russia, Saudi Arabia, South Africa, South Korea) during COVID-19 period. (**E**) The MFDFA results of daily index return time series (Turkey, UK, USA) during COVID-19 period.



(**A**)

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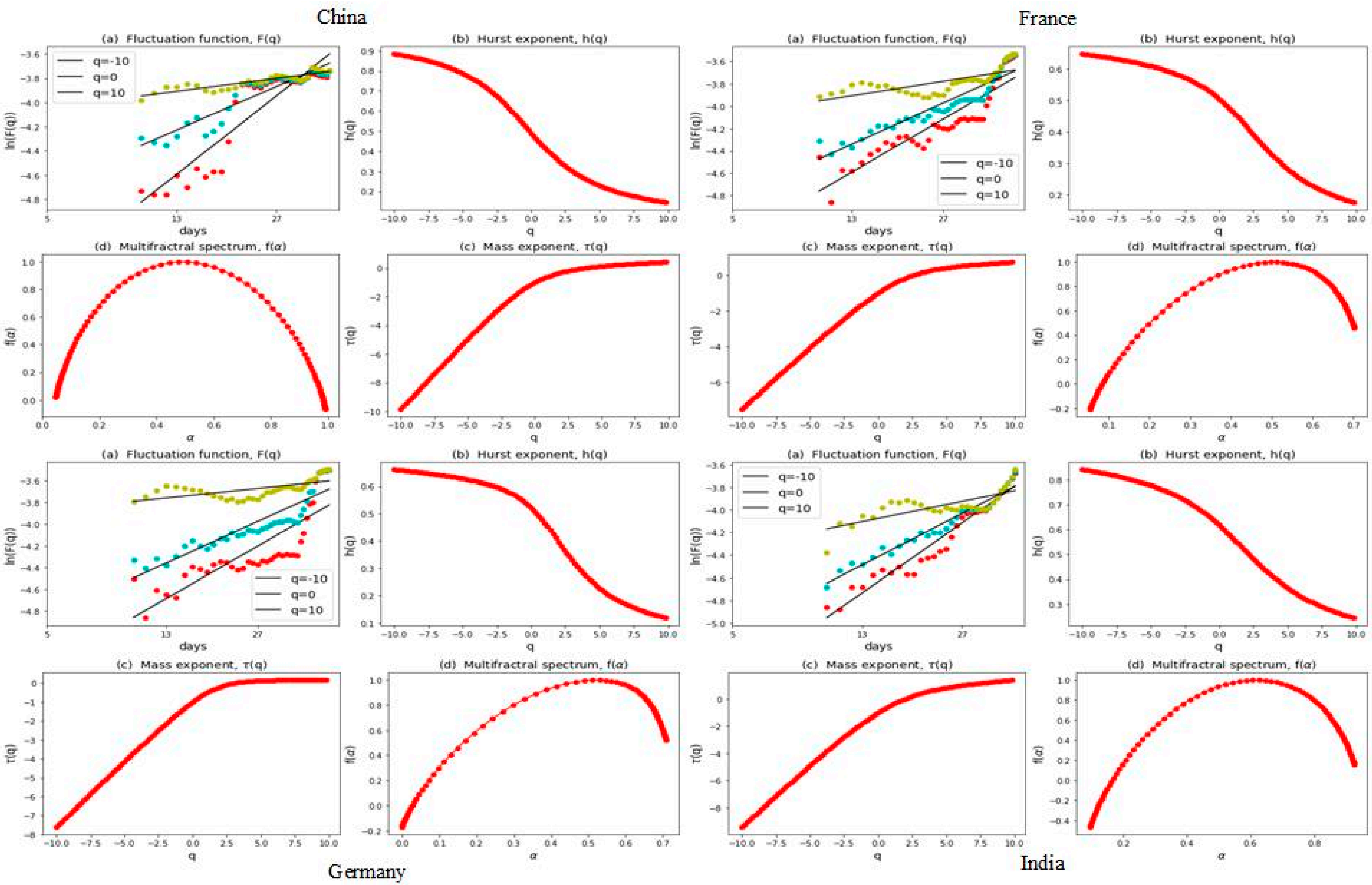

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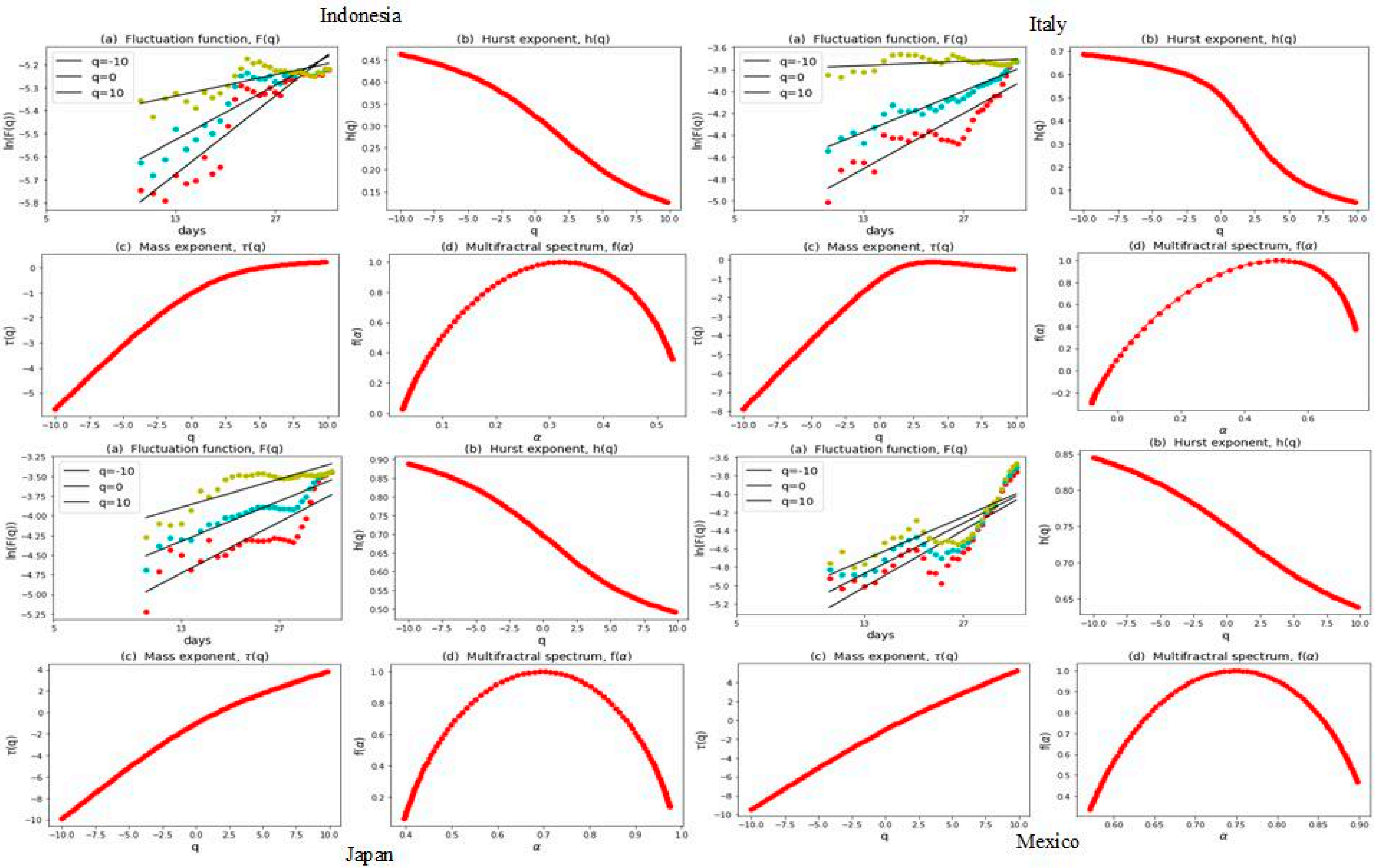

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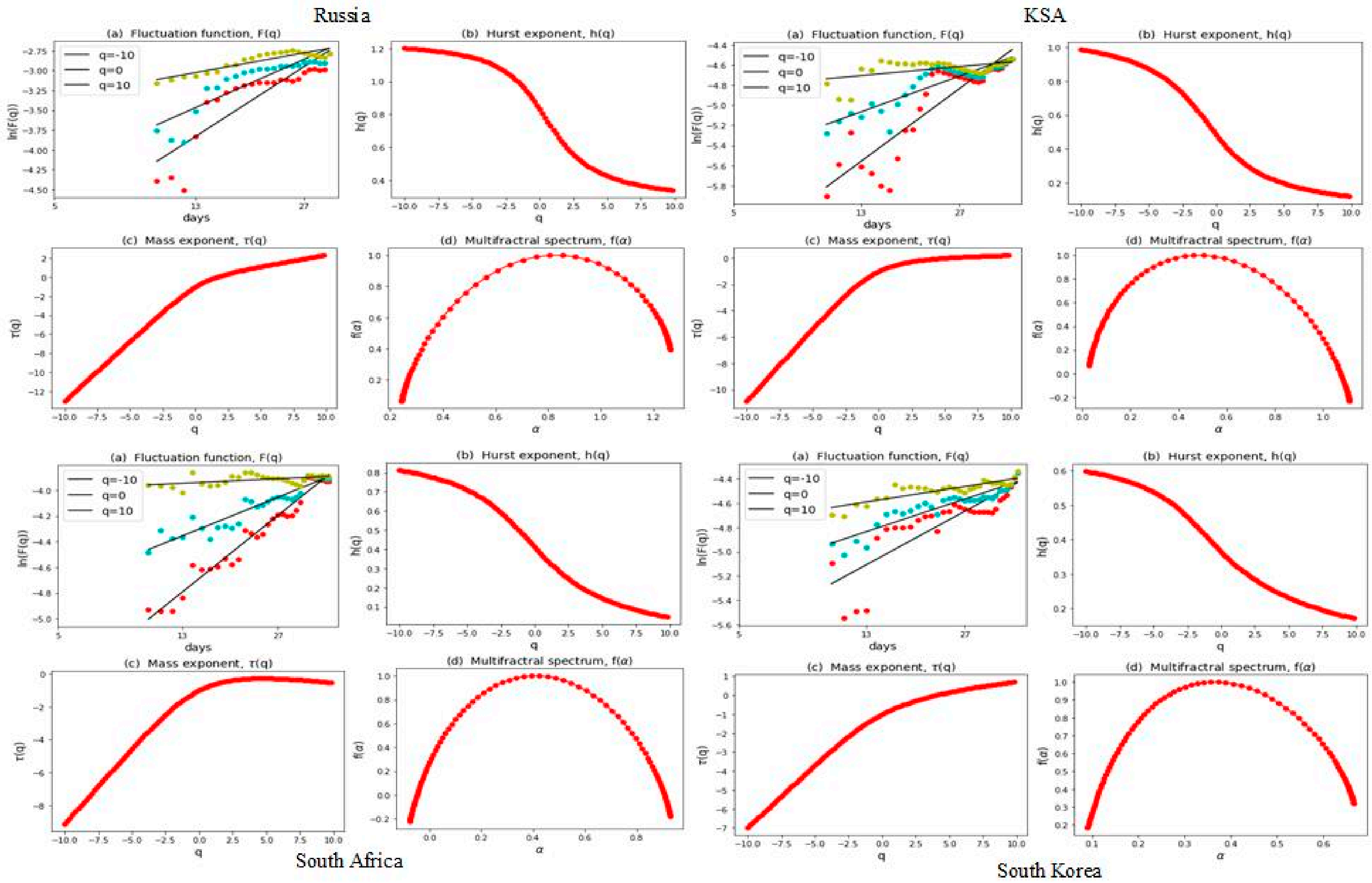

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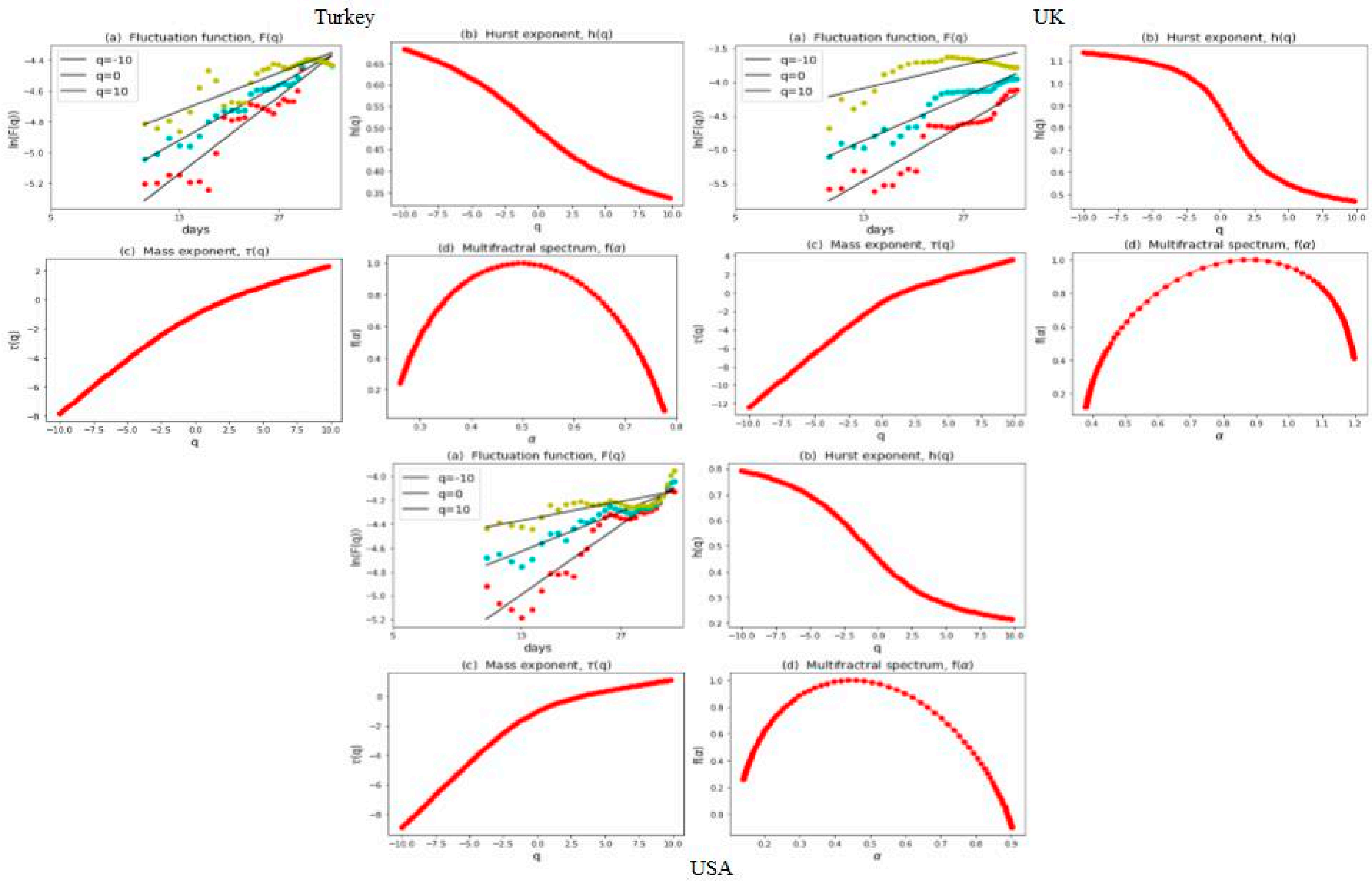

(**E**)

Figure 3. (**A**) The Russia–Ukraine war period's MFDFA results (Argentina, Australia, Brazil, Canada) of the daily index return time series including, (**a**) fluctuation functions q = −10 (light green), q = 0 (light blue), q = 10 (red), (**b**) generalized Hurst exponent q, (**c**) mass exponent $\tau(q)$, and (**d**) multifractal spectrum $f(\alpha)$. (**B**) The MFDFA results of daily index return time series (China, France, Germany, India) during Russia-Ukraine War period. (**C**) The MFDFA results of daily index return time series (Indonesia, Italy, Japan, Mexico) during Russia-Ukraine War period. (**D**) The MFDFA results of daily index return time series (Russia, Saudi Arabia, South Africa, South Korea) during Russia-Ukraine War period. (**E**) The MFDFA results of daily index return time series (Turkey, UK, USA) during Russia-Ukraine War period.

Table 4. Generalized Hurst exponents for G20 stock indices for the entire period of study and their range over q $\in [-10, 10]$.

Overall Period				**Developed Markets**									**Emerging Markets**						
Order q	**Australia**	**Canada**	**France**	**Germany**	**Italy**	**Japan**	**UK**	**USA**	**Argentina**	**Brazil**	**China**	**India**	**Indonesia**	**Mexico**	**Russia**	**Saudi Arabia**	**South Africa**	**South Korea**	**Turkey**
−10	0.627	0.642	0.635	0.619	0.720	0.737	0.631	0.610	0.772	0.630	0.747	0.615	0.744	0.654	0.492	0.798	0.604	0.661	0.541
−8	0.613	0.630	0.620	0.608	0.702	0.719	0.618	0.595	0.755	0.616	0.728	0.599	0.726	0.640	0.479	0.781	0.590	0.644	0.527
−6	0.595	0.615	0.600	0.595	0.677	0.695	0.599	0.575	0.732	0.598	0.702	0.577	0.702	0.622	0.462	0.759	0.572	0.621	0.509
−4	0.574	0.596	0.576	0.581	0.641	0.663	0.575	0.549	0.702	0.575	0.666	0.552	0.668	0.596	0.439	0.730	0.552	0.589	0.489
−2	0.555	0.571	0.547	0.567	0.598	0.626	0.540	0.517	0.662	0.542	0.622	0.528	0.623	0.557	0.409	0.698	0.529	0.538	0.469
0	0.533	0.530	0.515	0.549	0.556	0.592	0.488	0.473	0.608	0.494	0.569	0.509	0.565	0.494	0.360	0.668	0.499	0.458	0.442
2	0.479	0.455	0.477	0.518	0.464	0.562	0.418	0.404	0.535	0.428	0.499	0.473	0.490	0.421	0.265	0.620	0.448	0.366	0.387
4	0.401	0.364	0.435	0.480	0.331	0.530	0.350	0.329	0.456	0.358	0.437	0.422	0.422	0.366	0.152	0.564	0.388	0.297	0.326
6	0.342	0.298	0.399	0.449	0.258	0.497	0.302	0.275	0.396	0.309	0.394	0.381	0.376	0.329	0.083	0.524	0.340	0.253	0.284
8	0.305	0.256	0.372	0.426	0.217	0.471	0.270	0.239	0.356	0.277	0.365	0.354	0.347	0.305	0.045	0.497	0.308	0.223	0.256
10	0.281	0.230	0.353	0.410	0.192	0.452	0.248	0.216	0.330	0.257	0.344	0.334	0.327	0.287	0.021	0.478	0.287	0.204	0.237
Δh	0.346	0.413	0.282	0.210	0.528	0.284	0.383	0.394	0.442	0.373	0.403	0.281	0.418	0.367	0.471	0.320	0.317	0.457	0.304

Table 5. Generalized Hurst exponents for G20 stock indices during the crisis periods of COVID-19 outbreak and Russia–Ukraine War and their range over q $\in [-10, 10]$.

	Developed Markets								**Emerging Markets**										
Order q	**Australia**	**Canada**	**France**	**Germany**	**Italy**	**Japan**	**UK**	**USA**	**Argentina**	**Brazil**	**China**	**India**	**Indonesia**	**Mexico**	**Russia**	**Saudi Arabia**	**South Africa**	**South Korea**	**Turkey**
COVID-19																			
−10	0.6564	0.6293	0.6673	0.7224	0.5453	0.7240	0.5224	0.6512	0.6722	0.8053	0.4151	0.7475	0.7168	0.6234	0.8642	0.7495	0.6503	0.8800	0.7404
−8	0.6458	0.6093	0.6496	0.7072	0.5283	0.7036	0.5091	0.6343	0.6557	0.7851	0.4059	0.7307	0.7042	0.6078	0.8444	0.7314	0.6370	0.8595	0.7273
−6	0.6333	0.5808	0.6257	0.6866	0.5057	0.6753	0.4920	0.6106	0.6330	0.7576	0.3958	0.7084	0.6872	0.5873	0.8165	0.7065	0.6197	0.8307	0.7097
−4	0.6208	0.5391	0.5950	0.6581	0.4751	0.6373	0.4707	0.5756	0.6010	0.7209	0.3862	0.6798	0.6630	0.5604	0.7760	0.6706	0.5968	0.7900	0.6855
−2	0.6131	0.4803	0.5644	0.6190	0.4333	0.5923	0.4487	0.5204	0.5568	0.6745	0.3788	0.6481	0.6251	0.5258	0.7163	0.6167	0.5652	0.7348	0.6501
0	0.5970	0.4001	0.5343	0.5504	0.3730	0.5381	0.4239	0.4294	0.4957	0.6186	0.3679	0.6072	0.5532	0.4776	0.6529	0.5348	0.5119	0.6529	0.5935
2	0.4599	0.2941	0.4225	0.3795	0.2912	0.4311	0.3344	0.2992	0.4089	0.5508	0.3369	0.4866	0.3915	0.3998	0.4440	0.4301	0.3772	0.5025	0.5007
4	0.3139	0.1932	0.2967	0.2309	0.2156	0.3019	0.2286	0.1891	0.3143	0.4808	0.2949	0.3515	0.2190	0.3091	0.2907	0.3402	0.2018	0.3447	0.4028
6	0.2407	0.1261	0.2259	0.1576	0.1638	0.2219	0.1651	0.1241	0.2482	0.4278	0.2618	0.2778	0.1283	0.2430	0.2043	0.2818	0.1037	0.2557	0.3398
8	0.2010	0.0848	0.1857	0.1182	0.1300	0.1769	0.1281	0.0857	0.2081	0.3919	0.2389	0.2374	0.0804	0.2012	0.1553	0.2446	0.0513	0.2075	0.3021
10	0.1763	0.0580	0.1604	0.0939	0.1069	0.1491	0.1046	0.0609	0.1827	0.3674	0.2228	0.2122	0.0517	0.1739	0.1247	0.2194	0.0200	0.1784	0.2781
Δh	0.4801	0.5712	0.5069	0.6285	0.4384	0.5749	0.4178	0.5903	0.4895	0.4380	0.1923	0.5353	0.6651	0.4495	0.7394	0.5300	0.6302	0.7016	0.4623
Russia−Ukraine War																			
−10	0.8931	0.8874	0.6477	0.6612	0.6871	0.8880	1.1385	0.7921	0.7881	0.9552	0.8833	0.8418	0.4635	0.8443	1.2029	0.9856	0.8127	0.5979	0.6826
−8	0.8759	0.8718	0.6353	0.6503	0.6728	0.8678	1.1248	0.7652	0.7659	0.9389	0.8571	0.8222	0.4487	0.8322	1.1880	0.9552	0.7841	0.5814	0.6611
−6	0.8516	0.8473	0.6192	0.6364	0.6539	0.8400	1.1057	0.7240	0.7331	0.9169	0.8166	0.7956	0.4292	0.8170	1.1644	0.9074	0.7408	0.5560	0.6329
−4	0.8145	0.8019	0.5969	0.6175	0.6281	0.8018	1.0757	0.6592	0.6817	0.8866	0.7500	0.7581	0.4029	0.7981	1.1209	0.8266	0.6713	0.5142	0.5959
−2	0.7539	0.7055	0.5628	0.5870	0.5881	0.7530	1.0174	0.5628	0.5995	0.8448	0.6404	0.7020	0.3678	0.7753	1.0275	0.6857	0.5592	0.4467	0.5492
0	0.6618	0.5284	0.5052	0.5216	0.5087	0.6971	0.8797	0.4493	0.4835	0.7894	0.4908	0.6176	0.3231	0.7492	0.8302	0.4838	0.4103	0.3644	0.4960
2	0.5679	0.3502	0.4161	0.3970	0.3653	0.6373	0.6873	0.3557	0.3649	0.7248	0.3529	0.5094	0.2718	0.7217	0.5984	0.3189	0.2737	0.2976	0.4460
4	0.5067	0.2453	0.3211	0.2720	0.2225	0.5835	0.5774	0.2949	0.2783	0.6646	0.2607	0.4068	0.2213	0.6953	0.4651	0.2281	0.1788	0.2504	0.4062
6	0.4722	0.1902	0.2502	0.1923	0.1322	0.5420	0.5220	0.2570	0.2236	0.6192	0.2042	0.3302	0.1790	0.6721	0.3978	0.1762	0.1168	0.2161	0.3763
8	0.4516	0.1586	0.2043	0.1455	0.0799	0.5117	0.4896	0.2320	0.1887	0.5878	0.1685	0.2779	0.1470	0.6530	0.3602	0.1432	0.0750	0.1906	0.3537
10	0.4379	0.1384	0.1745	0.1164	0.0476	0.4896	0.4682	0.2144	0.1650	0.5658	0.1446	0.2421	0.1238	0.6377	0.3369	0.1207	0.0457	0.1715	0.3362
Δh	0.4552	0.7491	0.4732	0.5448	0.6395	0.3984	0.6703	0.5777	0.6231	0.3893	0.7387	0.5997	0.3398	0.2066	0.8659	0.8649	0.7670	0.4264	0.3464

4. Conclusions

This study evaluated the stock market efficiency and herding behavior of the G20 stock market indices through the multifractal detrended fluctuation analysis (MFDFA) method. By using the latest data (up to May 2022), we presented a thorough outlook of all the developed and emerging stock markets as classified by the MSCI for the top economies of the world. Overall, the full sample investigation shows strong evidence of multifractality in all the G20 stock markets. In addition, the results reveal a high level of multifractality and resultant low efficiency for the Italian stock market, while Germany and India demonstrate the lowest degree of multifractality. The results further show anti-persistence with no trace of herding behavior for six developed stock markets including the USA, Australia, Canada, France, Italy, and UK during the overall period of study, which means any change increase (decrease) in the return series of former time period would probably be followed by an inverse decrease (increase) in the time period afterwards. The remaining two developed stock markets of Japan and Germany show persistence with a trace of minor herding behavior, thus representing positive autocorrelation. Moreover, only the two stock markets of Argentina and Saudi Arabia confirm persistent behavior, while the rest of the nine emerging stock markets, namely Brazil, China, India, Indonesia, Mexico, Russia, South Africa, South Korea, and Turkey, represent negative autocorrelation (anti-persistent fluctuations).

Further, we asked how the global pandemic (COVID-19) and the Russia–Ukraine crises influence the complexity of the G20 stock markets. Therefore, the data are portioned into two sub-sample periods based on individual reporting of the first confirmed COVID-19 cases and the Russia–Ukraine War by every country. With regard to sub-sample results, we similarly detected the multifractality of all the G20 stock markets, contrary to the random process as proposed in the efficient market hypothesis. An immediate observation was a tremendous increase in the width of the generalized Hurst exponent Δh for almost all the G20 stock markets, except Italy and China. The result confirms a high level of unevenness in the local fluctuations of G20 stock markets considering the sheer magnitude and impact of the crises on the world stock markets. In addition, Russia and South Korea remain the least efficient, whereas the Mexican and Chinese stock markets appear to be more efficient markets among all G20 countries during the two crisis periods. Moreover, the results show anti-persistence and an absence of herding behavior for the majority of G20 stock markets during COVID-19, compared to the later period of the Russia–Ukraine War, which confirms the evidence of the persistence and herding behavior of many stock markets.

This study presents several implications. First, the results of this study offer opportunities for a wide range of audiences, including individual and institutional investors, portfolio managers, and practitioners, to understand the efficiency of the top 20 economies of the world, which is crucial for decision making. The G20 countries collectively account for a significant portion of global economic activity and trade. Examining the efficiency of their stock markets allows us to explore the interconnectedness and potential spillover effects between these markets. In addition, the comprehension of how shocks and market developments in one country propagate to others within the G20 can provide valuable insights into systemic risks, contagion effects, and global market dynamics. This knowledge can be critical for investors and policymakers seeking to manage risks effectively. Second, the results during the crisis periods of the Russia–Ukraine War and COVID-19 outbreak offer an opportunity to examine the presence of herding behavior to detect market bubbles and take positions accordingly. Third, the results of the crisis periods show a tremendous increase in generalized Hurst exponents, representing unevenness in the local fluctuations of G20 stock markets. This directs government agencies and policymakers to better devise sustainable policies and risk management to achieve stock market stability and growth. Forth, the results of less efficient markets offer an opportunity to those investors thriving to receive abnormal returns. Moreover, the comparative analysis of emerging and developed markets during the overall and crisis periods provides an opportunity to the authorities and regulators to consider varied stock market reactions to extreme events and design macro- and micro-prudential strategies accordingly. In addition, comparing the developed and emerging stock markets using the Hurst exponent is necessary to gain insights into market efficiency and predictability. This will allow public and private investors to understand the distinct characteristics and dynamics of different markets, facilitating more effective strategies and risk management approaches. Further research could be carried by examining the multifractality and efficiency of other countries on a time-varying scale to validate the findings achieved in this study. In addition, interesting future research could be conducted by applying the asymmetric MF-DFA method (Shahzad et al. 2020) on the G20 stock markets, especially in the pre- and post-Russia–Ukraine War period, to discuss any asymmetries with the results achieved in this study.

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