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Herding behavior during the Covid-19 pandemic: a comparison between Asian and European stock markets based on intraday multifractality

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Abstract

With the spread of Covid-19, investors' expectations changed during 2020, as well as financial markets' policy responses and the structure of global financial intermediation itself. These dynamics are studied in this paper, which analyzes quarterly changes in herding behavior by quantifying the self-similarity intensity of six stock markets in Asia and Europe. A multifractal detrended fluctuation analysis (MFDFA) is applied, using intraday trade prices with a 15-min frequency from Jan-2020 to Dec-2020. The empirical results confirm that Covid-19 had a significant impact on the efficiency of the stock markets under study, although with a quarterly varying impact. During the first quarter of the year, European stock markets remained efficient compared to Asian markets; in the subsequent two quarters, the Chinese stock market showed significant improvement in its efficiency and became the least inefficient market, with a decline in the market efficiency of the UK and Japan. Furthermore, European markets are more sensitive to asset losses than Asian markets, so investors are more likely to show herding in the former. Herding was at its peak during the 2nd quarter of 2020. These findings could be related to possible market inefficiencies and herding behavior, implying the possibility of investors forming profitable trading strategies.

Keywords Covid-19 · Fractals · Herding · High-frequent data · Multifractality

JEL Classification G14 · G15

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1 Introduction

The first 4 cases of coronavirus (Covid-19) were officially announced in Wuhan, China on December 31, 2019, and the disease has infected almost 80 million people and caused nearly 1.8 million deaths globally as of December 2020 (WHO, 2020). This novel virus has a mortality rate of nearly 6.07% in contrast to the mortality rate of influenza which is less than 1% (Gormsen & Koijen, 2020; Peters et al., 2020; WHO, 2020). The scale of the spread and trajectory of Covid-19 led the World Health Organization (WHO) to declare it as a global emergency on Feb 20, 2020 and then a pandemic on March 11, 2020. Black Swan events, like epidemics and terrorist attacks, cause shock, fear and panic among international investors and result in a sharp panic-selling response (Burch et al., 2016). Herding intensity rises during market stress moments due to the uncertainty. The Covid-19 pandemic, which is a clear public health issue, turned out to be also an unprecedented economic and financial crisis. The Covid-19 outbreak produces an environment of uncertainty and fear at the global level which has driven market movements (Aslam et al., 2020a; Lyócsa et al., 2020). In such an environment, investors who are less informed try to imitate the behavior of agents who have more information, leading to the psychological state of behavioral biases such as herding behavior.

Without adequate information, at the first sign of trouble, investors search for, and flee to safer havens. For instance, according to National Securities Depository Limited (NSDL) data, Foreign Portfolio Investors (FPIs) withdrew a huge amount of 247.76 billion and 140.50 billion rupees from Indian equity and debt markets in only 13 days from March 01, 2020 to March 13, 2020. In a recent study, Salisu and Akanni (2020) reveal that the increasing number of Covid-19 deaths and cases creates fear among investors due to its risk to health and economic activities worldwide. This fear of death and infection could lead to increased trading and herding behavior among stock market investors. The most common reasons for herding behavior include imperfect information, concerns about reputation and compensation structure (Bikhchandani & Sharma, 2000). More specifically in a crisis situation, uncertainty about the accuracy of private information increases, leading to price bubbles and informationally inefficient herding behavior. Moreover, the fear and panic regarding decreasing reputation and compensation in this period is also noted in the manager's ability to handle the portfolio, which results in herding behavior,especially if other investment professionals are in the same position.

The concept of herding is present in different research fields, including neurology, zoology, sociology, psychology, economics and finance, as mentioned by Spyrou (2013), who discusses it extensively, both theoretically and empirically. Herding is observed: because agents want to preserve their reputation (Graham, 1999; Rajan, 2006; Scharfstein & Stein, 1990; Trueman, 1994); irrational investors may herd due to psychological stimuli or restraints (Baddeley et al., 2004; Keynes, 1936); as a rational choice (Devenow & Welch, 1996; Froot et al., 1992), as rational arbitrage strategies (Shleifer & Summers, 1990); due to informational

cascades (Bikhchandani et al., 1992); due to investor sentiments (Barberis et al., 1998). Bikhchandani and Sharma (2000) distinguish between "spurious herding" as happens when investors make similar decisions based on a similar set of fundamental information and "intentional herding", when investors purposefully imitate the actions of others.

For instance, Scharfstein and Stein (1990) claim that through fear of losing their reputation, financial managers imitate the behaviors of others instead of using significant private information. This behavior could lead them to rational but socially inefficient herding behavior which might be perceived as protection against their underperformance (Rajan, 2006). Besides, herding can be a rational choice if investors (speculators) have short horizons and may herd on similar information, thus learning from the knowledge of other informed investors (Froot et al., 1992). This indicates that research resources are allotted in a non-optimal manner which may harm informational efficiency. Likewise, informational cascades take place if new entrants in the market prefer to ignore their own private information and imitate existing investors' trading strategies, assuming that those investors have better private information (Banerjee, 1992; Bikhchandani et al., 1992). Although herding can be understood as entirely rational, and may result in bubbles, some authors (Avery & Zemsky, 1998; Cipriani & Guarino, 2005; Drehmann et al., 2005) argue that it is not possible to create herding particularly in the form of an informational cascade but when simple information structures and price mechanism are considered. However, in the case of complex information structures, herding is viable and can affect the prices of most assets only when market uncertainty is high. Even experienced agents could move towards herding due to asymmetry and scarcity of information and common heuristic rules (Baddeley et al., 2004). Interestingly, arbitrageurs are regarded as entirely rational and noise traders (Shleifer & Summers, 1990) but exit the market when prices are near the top to collect their profits. Lastly, investor sentiments may also affect trading behavior and lead to systematic mispricing (Barberis et al., 1998).

In 1992, a new measure to analyze herding in financial markets was proposed: the Lakonishok, Shleifer and Vishny (LSV) measure (Lakonishok et al., 1992), and used later, for example by Uchida and Nakagawa (2007) or Tiniç et al. (2020). The LSV measure captures the extent to which fund managers deviate from average investment decisions depending upon overall economic conditions. According to the LSV measure, herding is defined as traders' tendency to accumulate on the same side and at the same time for a given specific stock, when an independent trade is expected (Lakonishok et al., 1992). It is commonly used to quantify institutional investor herding since it measures the imbalance in the numbers of buyers and sellers of each stock over a given period. However, this approach has certain drawbacks, for example, the assumption of short selling, considering a small number of investors involved in herding or the fact that it does not distinguish between managers who follow their own trading patterns and those who imitate the behavior of others (Sias, 2004; Wylie, 2005). For example, Bikhchandani and Sharma (2000) argue that LSV does not account for trading volume, and therefore, does not lessen the strength of herding. The herding measure proposed by Christie & Huang (1995) looks for only one form of herding and avoids other situations. In their approach, Christie and Huang (1995) applied a Cross-Section Standard Deviation (CSSD) model and argue

that in the case of herding behavior, the market dispersion from average returns is anticipated to be lower. For extreme market movements, investors tend to imitate the trading behavior of more informed senior agents. However, the major drawback of CSSD is that it can be easily influenced during periods of extreme movements (Tan et al., 2008). Therefore, it is hard to locate the presence of herding behavior in the usual conditions. Later, Chang et al. (2000) enhanced the measurement of dispersion and recommended the Cross-Section Absolute Deviation (CSAD) model.

Various studies incorporated both CSSD and CSAD models to examine the presence of market-wide herding behavior (Mnif et al., 2019). Some studies have shown that periods of instability and crises trigger trading behavior towards herding, and this was recurrent throughout the *global financial crisis* (GFC) and periods of bubbles (BenMabrouk & Litimi, 2018; BenSaïda, 2017; Litimi et al., 2016). Bowe and Domuta (2004) documented that foreign investors are more prone to herding behavior than domestic investors. Moreover, the existing literature on how pandemics influence herding behavior is limited, especially for Covid-19 (Goodell, 2020). For instance, Chang et al. (2020) examine the effect of the global financial crisis, SARS, and Covid-19 on energy stock markets by applying CSSD and CSAD approaches, concluding that herding behavior exists in stock markets because after the GFC investors have become more sensitive to losses. Therefore, during SARS and Covid-19, investors' panic has led them to sell their assets unwisely. Likewise, Espinosa-Méndez and Arias (2021) find evidence of an effect of Covid-19 on herding behavior in European capital markets by employing Cross-Section Standard Deviation (CSAD).

The stability of financial markets is crucial for secure and safe investments. The existence of volatility bubbles that are investigated by herding and other trading behaviors can originate market instability for a certain period. For this reason, changes in market prices and volatility can be examined by innovative financial tools based on mathematics heuristics (Li et al., 2014). Earlier models based on Gaussian distribution are not sufficient to forecast the trading behavior of financial markets. Therefore, this herding behavior can be well described by complex systems of fractals. In this context, Mandelbrot (1975) was the first to study the fractal theory that was later operationalized in finance to examine crises and crashes by Peters (1991). Fractal market analysis is a valuable tool as it gives an innovative framework to add precision modeling for the crisis, incoherence and non-periodicity that describe financial markets.

Detrended Fluctuation Analysis (DFA) and Multifractal Detrended Fluctuation Analysis (MFDFA) are two of the main approaches generally used in fractal market analysis. These methods examine the presence of dependence, distinguishing between persistency and anti-persistency in financial markets' behavior (Dewandaru et al., 2015). In non-stationary financial time series, DFA has been commonly used as a dynamic tool to identify long-range autocorrelations and correlations. The MFDFA approach is the generalized method of DFA that examines the multifractal pattern of financial time series (da Silva Filho et al., 2018). The effectiveness of these methods is reflected in examining the characteristics of multifractality, long-memory autocorrelations, and asymmetry of financial markets during crises (Hasan & Mohammad, 2015; Rizvi et al., 2014). Price variations in stocks could be

better explained through multifractal patterns which provide a more realistic view of market uncertainties. Moreover, fractals along with the scaling concept are best used for measuring price bubbles (Ghosh & Kozarević, 2019). Recently, Mnif et al. (2020) examined the herding behavior of the cryptocurrency market before and during Covid-19 by employing the technique of MFDFA with the Hurst Exponent and Magnitude of Long Memory (MLM), as suggested by Fernández-Martínez et al. (2017) and Khuntia and Pattanayak (2020).

Besides using the MFDFA, we calculate the correlation coefficient from the Detrended Cross-Correlation Analysis (ρDCCA) with the objective of analyzing the cross-correlation, in our case, between the Chinese and the other stock markets. We chose the Chinese stock market as the benchmark due to Covid-19 originating in this country, which will allow us to study the effect of the turmoil between markets. As we separate our data into the four quarters of 2020, it will also be possible to analyze the evolution of the cross-correlation between the specified markets during 2020.

We find a growing number of studies on the financial impacts of the Covid-19 pandemic. Recently, various themes have been developed, including financial networks (Aslam et al., 2020c; Zhang et al., 2020), stock market reactions (Aslam et al. 2020e, 2021; Haroon & Rizvi, 2020; Zhang et al., 2020), exchange rate fluctuation during the pandemic (Aslam et al., 2020b; Njindan Iyke, 2020), oil market reactions (Apergis & Apergis, 2020; Devpura & Narayan, 2020), air quality performance and multifractality (Ming et al., 2020; Sipra et al., 2021), insurance (Wang et al., 2020) and gold and cryptocurrencies (Corbet et al., 2020). The Covid-19 pandemic has also affected the efficiency of different financial markets. For instance, the intraday efficiency of European stock markets (Aslam et al., 2020d) and exchange rate markets (Aslam et al., 2020b) declined during the Covid-19 outbreak. Furthermore, Aslam et al. (2020e) reported that stock market efficiency varies with the evolution of Covid-19, with decreasing efficiency in February–March (2020) and a recovery in April–May (2020). Also, in the context of Covid-19, but applying the DCCA or its variants, Wang et al. (2020) showed the impact of Covid-19 on agricultural commodities, with an increase in the cross-correlations, while Chakrabarti et al. (2021) and Okorie and Lin (2021) find evidence of contagion effects in stock markets.

As far as we know, there is no comprehensive comparative study addressing the changes in herding behavior by incorporating the evolution of the Covid-19 pandemic. Though psychological factors cannot be directly observed, it is possible to detect herding behavior by quantifying the self-similarity intensity in stock markets. Therefore, we propose to analyze this effect on six stock markets, using Econophysics modeling. Econophysics is an interdisciplinary field of research covering a variety of approaches with its origin in statistical physics and being used to study economic and social phenomena (see, for example, Jovanovic & Schinckus, 2013). By filling this gap, this study contributes to the literature in three main aspects. Firstly, in order to reveal the new inner dynamics, it employs the high frequency, 15-min interval data of three Asian and three European markets. The Asian markets are India, China and Japan and the European markets are the UK, France and Spain, based on their high number of Covid-19 cases and deaths (WHO, 2020). Secondly, as Covid-19 spread, several changes occurred in investors' expectations, financial markets' policy responses and the structure of global financial intermediation,

during 2020. To incorporate these dynamics, this study investigates the quarterly changes in herding behavior through multifractality by employing the MFDFA technique of Kantelhardt et al. (2002) along with the Generalized Hurst Exponent. Thirdly, this study ranks the countries based on an index of Magnitude of Long Memory (MLM) to quantify the levels of herding and market efficiency quarterly, as proposed by Khuntia and Pattanayak (2020)

Our main findings show that Covid-19 had a significant but time-varying impact on the efficiency of Asian and European stock markets. During the first quarter of the year, the European stock markets remained efficient when compared to Asian markets, but in the subsequent two quarters, the Chinese stock market shows a significant improvement, with a decline in the market efficiency of the UK and Japan. Furthermore, European stock markets follow herding behavior as compared to Asian markets. Herding was at its peak during the 2nd quarter of 2020.

2 Data and Methodology

2.1 Data description

This study employs high-frequency intraday data from European (UK, France and Spain) and Asian equity markets (China, India and Japan). These indices are selected based on the total number of deaths and cases of Covid-19 and on the availablity of high-frequency data. Salisu and Akanni (2020) confirmed the presence of herding behavior by linking the increasing number of Covid-19 deaths and cases with fear among investors. In Asian markets, the highest level of Covid-19 cases and deaths are reported in India, whereas the UK is the most affected country in the European region (WHO, 2020). To reveal the inner dynamics and herding behavior, high-frequency, 15-min interval data were collected for the period ranging from January 01, 2020 to December 03, 2020 (it was not possible to access data from 2019 to compare the periods before and after Covid-19). Furthermore, to explore the changes in investors' expectations as Covid-19 evolved, quarterly changes in herding behavior are estimated by dividing the data into the four consecutive quarters of 2020. During data cleaning, duplicate prices which lead to zero returns were deleted. After data cleaning, the exact number of observations for each quarter in each country is given in Table 1, along with the selected index symbol.

Intraday returns (15-min) are calculated with the usual logarithm difference, i.e.

$$r(t) = \ln\left(\frac{p_t}{p_{t-1}}\right) \times 100, \tag{1}$$

with $p(t)$ being the price of a given index at time t.

2.2 Multifractal detrended fluctuation analysis–MFDFA

MFDFA is proposed by Kantelhardt et al. (2002) to examine the multifractality of non stationary financial time series, a methodology based on the one dimesional

Table 1 List of countries, corresponding stock index and quarterly number of observations. Source: Author's own calculations

S. No.	Country	Index symbol	Observations (15-minute interval)			
			Quarter 1	Quarter 2	Quarter 3	Quarter 4[a]
Asia						
1	China	FTSE China A50	4856	4932	5009	3198
2	India	NIFTY 50	4464	4558	4558	2977
3	Japan	Nikkei 225	5549	5427	5761	3715
Europe						
4	UK	FTSE 100	5558	5620	5746	3717
5	France	CAC 40	3580	3472	3696	2002
6	Spain	IBEX 35	3069	2974	3168	2014

[a]Quarter 4 ranges from 01-Oct-2020 till 03-Dec-2020

DFA method proposed by Peng et al. (1994). MFDFA consists of the five steps given below. Considering a time series x_i of length N and with i ranging from 1 to N, the first step of MFDFA consists of obtaining the cumulative sum or profile of $Y(i)$, i.e.,

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

with $\bar{x}$ being the mean of the whole time series. Through this step the white noise process is converted into a random walk. In the second step, the Y_t profile is divided into the segments $N_s \equiv \frac{N}{s}$ of the same length s. The third step consists of calculating the local trend $(\tilde{Y}_v)$, with the ordinary least squares fitting polynomial for any segment of length v, which is then used to detrend the profile, i.e.,

$$F_S^2(v) = \frac{1}{s} \sum_{k=1}^{s} \left(Y_V(k) - \tilde{Y}v(k) \right)^2 \tag{3}$$

The detrending process is repeated over the whole range of windows of s size and then the average segments are drawn to the fluctuation function of F_q to the qth order in the fourth step, i.e.,

$$F_q(S) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2Ns} [F_s^2(v)][F_s^2(v)]^{\frac{q}{2}} \right\}^{1/q} \tag{4}$$

where q is not equal to zero.

The last step is the log–log regression between $F_q(s)$ and s in order to identify the scaling behavior of the fluctuation functions for each value of q and s, which has a power-law given by

$$F_q(s) \propto S^{H(q)} \tag{5}$$

Lashermes et al. (2004) recommended selecting the order at $m = 1$ in order to avoid over fitting, and this approach is followed here.

2.3 Generalized Hurst exponent–GHE

Hurst (1951) proposed the Hurst Exponent, a measure which is used to identify the type of persistence of a given phenomenon. More specifically, when the value of $h(q)$ is less than 0.5, a given time series has an anti-persistent behavior, lesser fractal quotient, with no shape and without the existence of herding behavior, in the context of financial time series. When the value of $h(q)$ is equal to 0.5, it shows that the financial time series are of a stochastic nature and follow a random walk. Finally, when $h(q)$ is greater than 0.5, it means that the financial time series under analysis exhibits a higher fractal quotient, with the possible presence of herding behavior. The roughness of the financial time series introduced by Mandelbrot(1963) is quantified with the estimation of the Holder exponent (H) (Mandelbrot 1963; Mandelbrot & Van Ness, 1968) and several authors used the Hurst exponent to measure market efficiency (Caraiani, 2012; Domino, 2011).

The fractal dimension (d) can be defined as:

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

and

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

The function of scaling for multifractal process $\tau(q)$ is linear for the process of mono fractals but concave for multifractals. There are two methods to calculate $\tau(q)$: the Generalized Hurst Exponent (GHE) and the generalized fractal dimension (GFD).

From GHE we could have

$$H(q) = \frac{1 + \tau(q)}{q} \tag{8}$$

and from the GFD we have

$$D(q) = \frac{\tau(q)}{q - 1} \tag{9}$$

The GHE method is mainly based on the geometry of fractals (Di Matteo, 2007). The Hurst analysis examines if some statistical properties of time series $X(t)$ (with $t = \nu, 2\nu,..., k\nu,..., T$) scale with the time resolution (ν) and the observation period (T). In this case, the qth order moment $K_q(\mu)$ of the distribution of increment $X(t)$ can be characterized as follows:

$$K_q(\mu) = \frac{\langle |X(t + \mu) - X(t)|^q \rangle}{\langle |X(t)|^q \rangle} \tag{10}$$

where the time interval μ can vary between ν and μ_{max}.

From the scaling behavior $K_q(\mu)$, the generalized Hurst exponent $H(q)$ can be defined as follows (Groenendijk et al., 1998).

$$K_q(\mu) \sim \alpha \mu^{qH(q)} \tag{11}$$

$$\alpha = \left(\frac{\mu}{\nu} \right) \tag{12}$$

Considering Eq. (11) and from the Lagendre transform it is possible to write:

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

Hence, the spectrum of singularity $f(\alpha)$ can be identified as:

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

The GHE range is examined by:

$$\Delta H \equiv \max qH(q) - \min H(q) \tag{15}$$

whereas the multifractal spectrum width is estimated to examine the multifractality level and can be shown as:

$$\Delta \alpha \equiv \max q\alpha(q) - \min q\alpha(q) = h(-\infty) - h(+\infty) \tag{16}$$

For analysis purpose, the range of scaling is set from $s_{min} = 10$ and $s_{max} = (T/5)$, where T is the length of financial time series.

2.4 Magnitude of long memory index–MLM

In order to compute the efficiency level of financial markets, the magnitude of long memory index (MLM) is examined, being related with the GHE. Based on multifractal dimension, this index reveals that the fluctuations comprising smaller $H(-10)$ and larger $H(+10)$ follow the random walk process. The stock market returns will exhibit absolute efficiency without any long memory and herding behavior at MLM=0. In the same way, lower levels of MLM refer to lower herding behavior and long memory, while higher levels of MLM indicate higher levels of herding behavior and long memory. Finally, the MLM inefficiency index recommended by Khuntia and Pattanayak (2020) can be described in the following equation as:

$$\text{Magnitude of Long} - \text{memory(MLM)} = \frac{(|h(-10) - 0.5| + |h(10) - 0.5|)}{2} \tag{17}$$

2.5 Detrended cross-correlation analysis correlation coefficient (ρDCCA)

The DCCA, proposed by Podobnik and Stanley ([2008](#)), is a methodology created to assess the long-range cross-correlation between two different time series, even in the context of non-stationary time series. The different steps of the DCCA are similar to those of the DFA. Based on two different time series Y_i and X_i of the same length k = 1, 2, ..., N, the DCCA starts by calculating the profiles

$$Y_k = \sum_{i=1}^{k} \left(y_i - y\right) \text{ and } X_k = \sum_{i=1}^{k} \left(x_i - x\right) \tag{18}$$

with $\langle . \rangle$ being the mean operator. The procedure goes on to divide the profiles in (N–n) overlapping boxes, starting in $n = 4$ and ending with $n = \frac{N}{4}$. Based on the ordinary least squares, the trends $\tilde{Y}_{k,i}$ and $\tilde{X}_{k,i}$ are then calculated, which will be used to detrend the profiles Y_k and X_k and used to calculate the covariance of the residuals for each box, given by

$$f_{xy}^2(n, i) = \frac{1}{(n+1)} \sum_{k=1}^{i+n} \left(X_k - \tilde{X}_{k,i}\right)\left(Y_k - \tilde{Y}_{k,i}\right) \tag{19}$$

and used to calculate the DCCA covariance, considering the whole set of $N - n$ boxes, given by

$$F_{xy}^2(n) = \frac{1}{(N-n)} \sum_{i=1}^{N-n} f_{xy}^2(n, i) \tag{20}$$

Based on the information from Eq. ([20](#)), and with similar information to the original DFA proposed by Peng et al. ([1994](#)), Zebende ([2011](#)) proposes the ρ_{DCCA} defined by

$$\rho_{DCCA} = \frac{F_{xy}^2(n)}{F_x^2(n)F_y^2(n)} \tag{21}$$

This ρ_{DCCA} is a non-linear correlation coefficient, verifying the important relationship of $-1 \leq \rho DCCA \leq 1$ and having several relevant properties (see, for example, Kristoufek, [2014a](#), [b](#); Zhao et al. [2017](#)). The procedure proposed by Podobnik et al. ([2011](#)) is used to test the significance of the correlations.

To apply the ρ_{DCCA}, and because the indices do not have the same trading moments, we had to match the observations, implying that the number of observations is not equal. However, as we are dealing with intraday data, we have enough information to perform the ρ_{DCCA}, ranging from 2402 observations for the China-Spain pair, in the fourth quarter of 2020, to 4800 observations for the China-Japan pair, in the third quarter.

Table 2 Summary Statistics of intraday log returns

	India	China	Japan	France	Spain	UK
Average						
Q1	− 0.0073	− 0.0024	− 0.0035	− 0.0082	− 0.0105	− 0.0049
Q2	0.0041	0.0021	0.0035	0.0042	0.0027	0.0020
Q3	0.0024	0.0020	0.0008	− 0.0006	− 0.0020	− 0.0008
Q4	0.0049	0.0033	0.0038	0.0079	0.0099	0.0025
Standard deviation						
Q1	0.3747	0.2623	0.3325	0.4626	0.4753	0.3353
Q2	0.2462	0.1366	0.1948	0.2721	0.2915	0.1866
Q3	0.1260	0.1715	0.1098	0.1691	0.2000	0.1299
Q4	0.1341	0.1294	0.1103	0.2188	0.2413	0.1423
Minimum						
Q1	− 4.7615	− 3.5166	− 6.2136	− 8.9549	− 7.1190	− 6.4784
Q2	− 1.6723	− 0.9665	− 2.1163	− 3.3480	− 2.6460	− 1.2766
Q3	− 0.8286	− 1.2743	− 2.4889	− 1.1791	− 1.5422	− 1.0770
Q4	− 0.7636	− 1.4746	− 0.7555	− 2.6137	− 1.9941	− 1.1716
Maximum						
Q1	4.2696	2.6103	3.0961	5.2026	5.2242	3.8100
Q2	4.4738	1.5329	2.6050	4.9761	4.6949	1.6591
Q3	0.7481	1.7825	1.0915	1.6528	1.7846	0.8985
Q4	0.9617	1.1497	2.4437	3.9570	4.9041	2.7884
Skewness						
Q1	− 0.2032	− 0.2048	− 2.1474	− 2.3974	− 2.0083	− 2.2137
Q2	1.9566	0.7336	0.1157	1.5923	1.3888	− 0.1940
Q3	− 0.5202	0.3556	− 1.8361	0.2384	− 0.0212	− 0.1978
Q4	− 0.2693	− 0.2829	2.8214	2.3175	4.4954	2.2051
Kurtosis						
Q1	29.6308	18.3281	54.1196	71.7757	53.4193	52.4392
Q2	37.2672	11.6432	13.4189	53.2159	36.0092	6.2772
Q3	4.7834	11.4103	50.0632	6.3260	7.4377	4.2999
Q4	5.9727	16.5195	68.1672	68.5458	94.2872	45.1559
Jarque–Bera						
Q1	162,919***	67,839***	680,087***	769,501***	365,635***	640,074***
Q2	267,718***	28,237***	40,626***	409,584***	165,572***	9236.1***
Q3	4536.5***	20,000***	587,718***	6171.5***	6858***	4451.6***
Q4	4438.2***	36,243***	758,284***	391,191***	774,784***	317,787***

*** denotes significance at 1% level

3 Results and discussions

3.1 Preliminary results

Table 2 presents the descriptive statistics on a quarterly basis of intraday returns for

the selected indices. The results show that in the first quarter of the Covid-19 out-break, the average returns for all the sample countries are negative, with the maximum average loss suffered by France and the minimum by Spain. These negative average returns in all the sample countries become positive in the second quarter. The returns in the third quarter show an interesting trend with positive values in Asian markets, whereas the three European markets suffered losses, which could be related to the epicenter of the disease moving to Europe. In the last quarter it is interesting to observe that all the markets showed positive average returns with the lowest return in Spain and France, probably a response to the economic measures all over the world and confidence arising from news about a vaccine. The European countries show the highest losses (minimum returns) in the first quarter which were clearly reduced in the last two quarters. The lowest intraday losses are observed in India and Japan in the third and fourth quarters. Spain and France show the highest maximum returns in the first quarter, confirming them as the most volatile markets, which is surely related to how the first wave affected these countries. The evolution of the standard deviations indicate that the first quarter showed the highest volatility, clearly related to the instability and uncertainty caused by Covid-19 which ended in the pandemic being declared in the middle of March.

The skewness for all series was negative for all the indices in the first quarter, with high values for Japan, France, Spain and the UK, meaning that more negative returns were observed. In the second quarter, only the UK showed negative skewness, although at a lower level. In the third quarter, most skewness values are negative. In the last quarter, India and China show negative skewness while the remaining indices have positive and relatively high levels for this measure, meaning that this was a recovery quarter. These findings demonstrate the presence of fear and extremely negative outcomes at the beginning of the Covid-19 crisis, although in the last quarter the sentiment seems to be inverted. The extreme variations are confirmed by kurtosis levels that are greater than the reference value of normal distribution, indicating that all returns exhibit fat tail behavior, which is one of the stylized facts of financial time series (Cont, 2001; Parisi et al., 2013). Still regarding kurtosis levels, we can see they are time-varying, for the different quarters in analysis, but also vary across countries, with the results being related firstly to the impact of the beginning of the health crisis on stock markets (kurtosis levels are high for all stock markets during the first half of 2020) but also to the evolution of the disease in those countries. For example, the kurtosis of the Chinese stock market is relatively stable and higher during the first quarter, but then decreased, in a country where Covid-19 was relatively controlled. For the remaining countries, after a decrease in kurtosis levels, at the end of the year those levels rose again. At the same time, those countries saw some changes in the evolution of Covid-19 infections, which rose from the third quarter. For example, the UK had high kurtosis in the first quarter, related to the turmoil at the start of Covid-19 but then just in the last quarter of 2020, as the Covid-19 situation became more severe after mid-September. Overall, the skewness and kurtosis values confirm evidence of asymmetry and fat tails behavior. Furthermore, significant Jarque–Bera statistics confirm non-normality of the data. The evidence of fat tails supports the possibility of the Fractal Market Hypothesis (Peters, 1996), which is based on scaling properties of distribution, in contrast to the
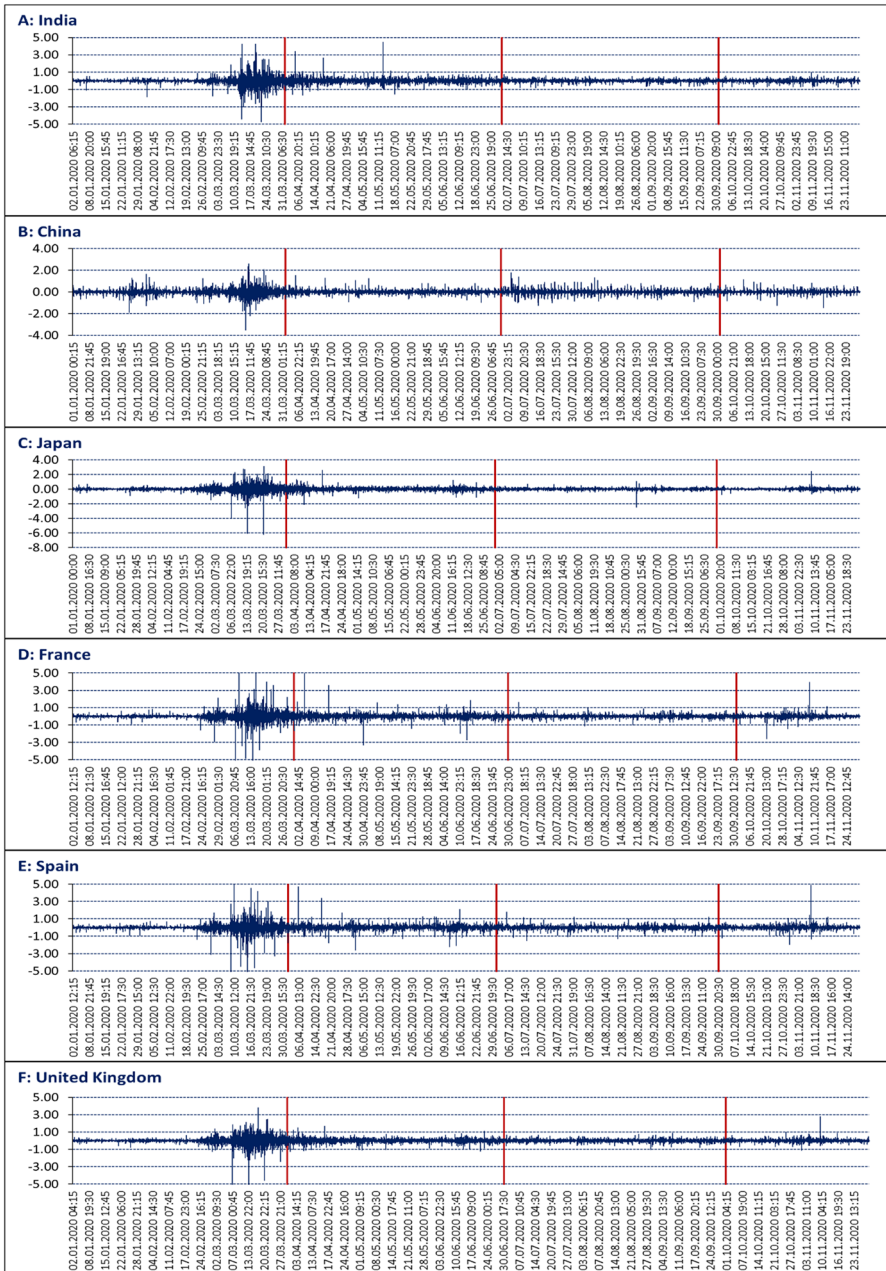
Fig. 1 Quarterly evolution of Intraday (15-min) return fluctuation from 01-Jan-2020 to 02-Dec-2020

information efficiency of the Efficient Market Hypothesis proposed by Fama (1970). Therefore, the effectiveness of employing MFDFA on fat tailed data to examine herding is more appropriate and justifiable especially in turmoil periods such as

Covid-19. Figure 1 shows the quarterly evolution of Intraday return fluctuation from 01-Jan-2020 to 03-Dec-2020.

In the context of Covid-19, high volatility levels could be related with investors' fear. As previously mentioned in interpreting the descriptive statistics of Table 2, the volatility of returns decreased in the second and third quarter, with the exception of China, whose return volatility increased in the third quarter. Later, all the markets except the Chinese one showed increased volatility in the fourth quarter. Consulting the CBOE Volatility Index (VIX), a popular indicator of volatility, fear and market turbulence (Carr, 2017; Whaley, 2000), we can see an abrupt rise in its value, reaching 82 right after the declaration of COVID-19 as a pandemic. Regarding mean values, VIX rose from 15.38 in 2019 to a value of 29.25 in 2020, confirming the surge of fear in markets.

3.2 Multifractality and market efficiency

The results of applying the MFDFA for each quarter are presented in Figs. 2, 3, 4, 5. For illustration purposes, and taking the example of India, we can see in panel a) the log–log relationship between the fluctuation function (F_q) and s, for 21 different settings and with the colored dots for various orders, namely $q = -10$ (green), $q = 0$ (blue), and $q = 10$ (black). There, we can see a well-shaped form and possibly represented by a straight line. In panel b), we find the value of the generalized Hurst Exponent $h(q)$ with q ranging from -10 to $+10$, used to explain the effects of small and large variations, respectively. The value of $h(q)$ is dependent on q and confirms the presence of multifractality in the stock market returns' series. The findings
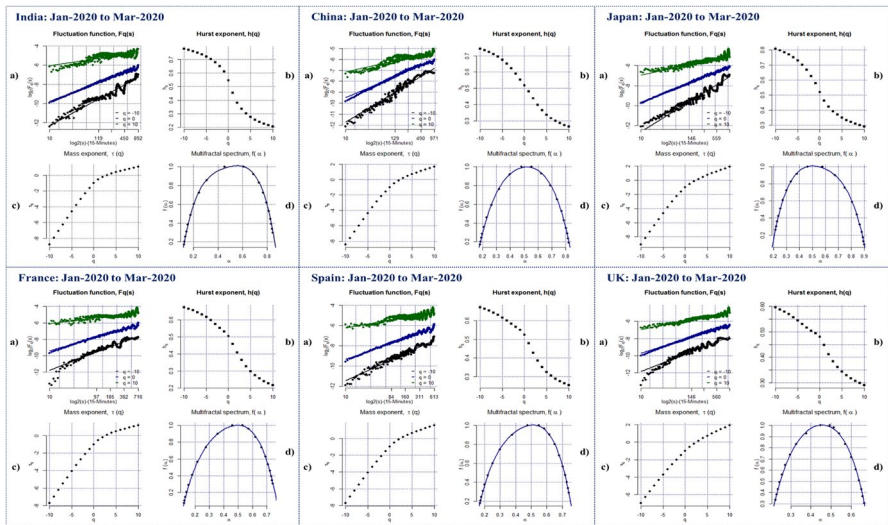

Fig. 2 MFDFA results of intraday stock returns of Asian and European region for the 1st Quarter. **a** Fluctuation function for q from -10 to 10; **b** generalized Hurst exponent depending on q; **c** mass exponent; **d** multifractal spectrum
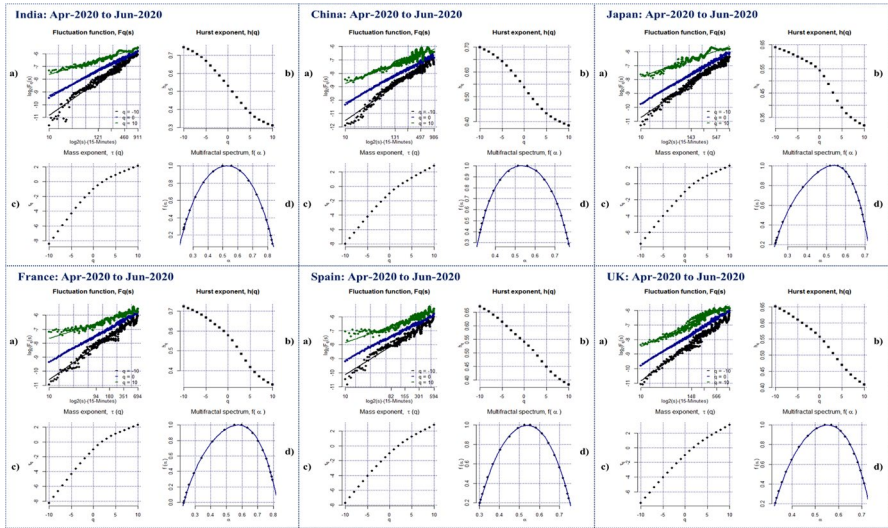
Fig. 3 MFDFA results of intraday stock returns of Asian and European region for the 2nd Quarter. **a** Fluctuation function for q from − 10 to 10; **b** generalized Hurst exponent depending on q; **c** mass exponent; **d** multifractal spectrum

Fig. 4 MFDFA results of intraday stock returns of Asian and European region for the 3rd Quarter. **a** Fluctuation function for q from − 10 to 10; **b** generalized Hurst Exponent depending on q; **c** mass Exponent; **d** multifractal spectrum
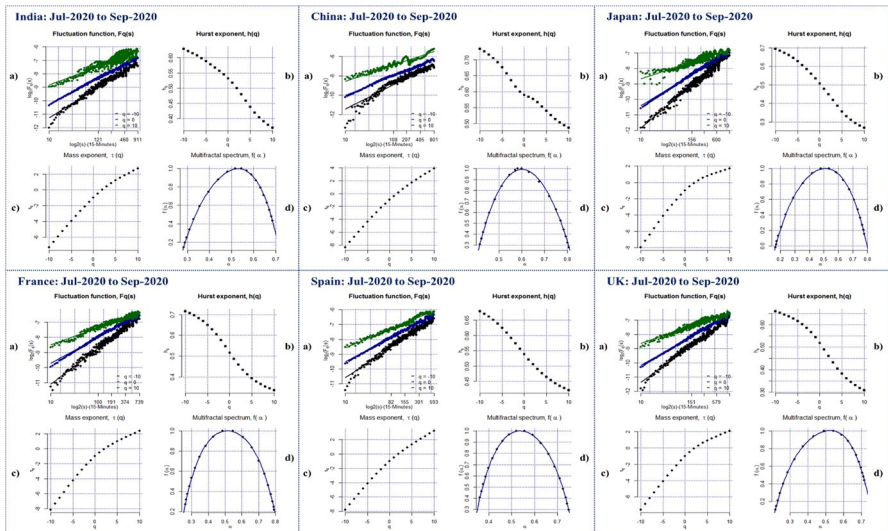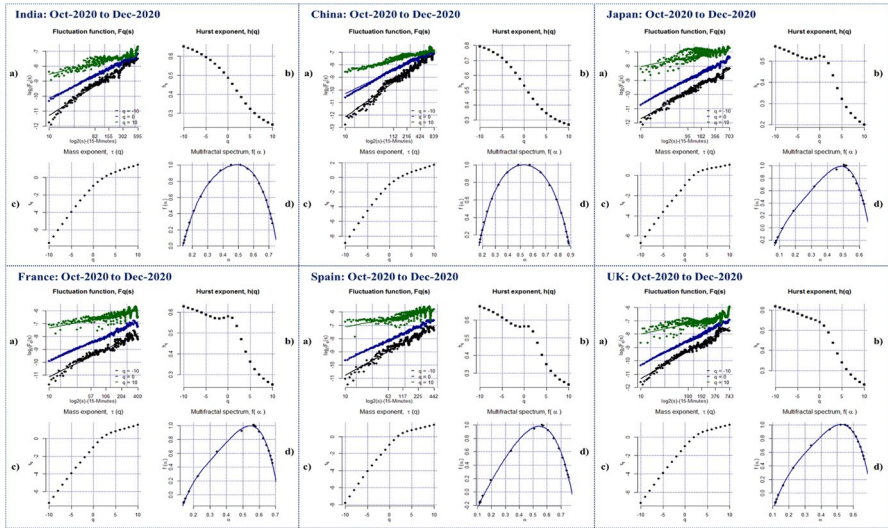
Fig. 5 MFDFA results of intraday stock returns of Asian and European region for the 4th Quarter. **a** Fluctuation function for q from -10 to 10; **b** generalized Hurst exponent depending on q; **c** mass exponent; **d** multifractal spectrum

confirm a declining pattern of $h(q)$ in Asian and European markets for all quarters, which means the presence of a multifractal pattern. The stock market series multifractality results are confirmed in Table 3.

For instance, in the first quarter, for the Indian stock market, the highest value of $h(q)$, is 0.78 for $q = -10$, falling to 0.55 at $q = 0$ and with the lowest value of 0.21 for $q = 10$. Likewise, in France, the highest value of $h(q)$ is 0.67 for $q = -10$, declining to 0.50 at $q = 0$ and with the lowest value of 0.22 for $q = 10$. This declining trend confirms the presence of patterns of multifractality in the time fluctuations in the stock markets under consideration. Similar declining trends are found in other Asian and European stock markets. Panel c) shows the Renyi exponent, $\tau(q)$, which is nonlinear for multifractal time series. For the Indian stock market in Q1, $\tau(q)$ presents an exponential shape, confirming again the existence of multifractality. Finally, panel d) depicts the plots of α versus $f(\alpha)$ representing the "multifractal spectrum" described by a single-humped shape, once again confirming the presence of multifractality.

From the graphical analysis, the presence of multifractality in all stock markets is confirmed. However, the degree of multifractality varies among these markets and changes can be observed in different quarters of 2020. The range of the generalized Hurst Exponent (Δh) implies different degrees of multifractality, with higher values indicating higher multifractality, while lower levels mean higher efficiency behaviors. The results of Δh and the width of the multiple spectrum ($\Delta \alpha$), as well as the efficiency ranking, are presented in Table 4.

In the first quarter, the Asian markets show higher levels of multifractality than the European stock markets. The highest range of the generalized Hurst exponent

Table 3 Generalized hurst exponent for Asian and European stock markets ranging from $-10 < Q < 10$

Order Q	Quarter 1						Quarter 2						Quarter 3						Quarter 4					
	India	China	Japan	France	Spain	UK	India	China	Japan	France	Spain	UK	India	China	Japan	France	Spain	UK	India	China	Japan	France	Spain	UK
−10	0.78	0.74	0.81	0.67	0.67	0.60	0.74	0.70	0.64	0.72	0.67	0.66	0.63	0.73	0.69	0.71	0.68	0.65	0.65	0.79	0.57	0.63	0.68	0.62
−9	0.77	0.73	0.80	0.66	0.66	0.59	0.73	0.69	0.63	0.72	0.67	0.65	0.62	0.73	0.68	0.71	0.67	0.64	0.64	0.78	0.56	0.62	0.67	0.61
−8	0.76	0.72	0.79	0.65	0.65	0.58	0.72	0.68	0.63	0.71	0.66	0.65	0.61	0.72	0.67	0.70	0.66	0.64	0.63	0.77	0.55	0.61	0.66	0.61
−7	0.75	0.71	0.77	0.64	0.64	0.57	0.71	0.67	0.62	0.69	0.65	0.64	0.61	0.71	0.66	0.68	0.65	0.63	0.62	0.76	0.54	0.61	0.65	0.60
−6	0.74	0.69	0.75	0.63	0.63	0.56	0.69	0.66	0.61	0.68	0.64	0.63	0.60	0.69	0.65	0.67	0.63	0.62	0.61	0.74	0.54	0.60	0.63	0.59
−5	0.72	0.68	0.73	0.62	0.62	0.54	0.67	0.64	0.60	0.67	0.63	0.62	0.59	0.68	0.63	0.65	0.61	0.61	0.60	0.72	0.53	0.59	0.62	0.58
−4	0.70	0.65	0.70	0.60	0.60	0.53	0.64	0.62	0.59	0.65	0.61	0.60	0.58	0.66	0.61	0.63	0.60	0.60	0.58	0.69	0.52	0.58	0.60	0.57
−3	0.68	0.62	0.67	0.58	0.58	0.52	0.62	0.61	0.58	0.63	0.60	0.59	0.57	0.64	0.58	0.60	0.58	0.59	0.56	0.66	0.51	0.57	0.58	0.57
−2	0.65	0.59	0.63	0.55	0.57	0.50	0.59	0.58	0.57	0.62	0.58	0.57	0.56	0.62	0.56	0.58	0.57	0.58	0.54	0.62	0.51	0.57	0.57	0.56
−1	0.61	0.55	0.58	0.53	0.55	0.49	0.56	0.56	0.56	0.60	0.57	0.54	0.54	0.60	0.53	0.55	0.55	0.57	0.51	0.57	0.52	0.57	0.56	0.55
0	0.55	0.52	0.52	0.50	0.52	0.48	0.53	0.54	0.54	0.58	0.55	0.52	0.53	0.59	0.51	0.52	0.54	0.56	0.49	0.53	0.52	0.58	0.57	0.54
1	0.45	0.48	0.46	0.46	0.48	0.45	0.50	0.51	0.52	0.55	0.52	0.49	0.52	0.58	0.48	0.49	0.53	0.54	0.45	0.48	0.52	0.57	0.56	0.52
2	0.38	0.44	0.42	0.41	0.43	0.41	0.47	0.49	0.49	0.52	0.51	0.46	0.50	0.58	0.45	0.46	0.51	0.52	0.42	0.44	0.49	0.53	0.54	0.49
3	0.34	0.40	0.39	0.36	0.38	0.38	0.44	0.47	0.45	0.48	0.49	0.43	0.48	0.57	0.42	0.43	0.49	0.51	0.38	0.40	0.43	0.47	0.47	0.44
4	0.30	0.36	0.37	0.33	0.35	0.36	0.41	0.45	0.42	0.45	0.48	0.41	0.46	0.55	0.39	0.41	0.47	0.49	0.35	0.37	0.37	0.41	0.40	0.39
5	0.28	0.34	0.35	0.30	0.33	0.34	0.38	0.43	0.39	0.42	0.46	0.38	0.44	0.54	0.36	0.39	0.45	0.47	0.32	0.34	0.32	0.36	0.35	0.34
6	0.26	0.32	0.33	0.27	0.30	0.33	0.36	0.42	0.37	0.39	0.45	0.36	0.42	0.53	0.33	0.38	0.43	0.45	0.30	0.32	0.28	0.33	0.31	0.31
7	0.24	0.30	0.32	0.26	0.29	0.32	0.34	0.41	0.35	0.37	0.44	0.34	0.40	0.51	0.31	0.36	0.42	0.44	0.28	0.30	0.25	0.30	0.28	0.28
8	0.23	0.29	0.31	0.24	0.27	0.31	0.33	0.40	0.34	0.35	0.44	0.33	0.39	0.50	0.29	0.35	0.40	0.43	0.26	0.29	0.23	0.28	0.26	0.26
9	0.22	0.27	0.30	0.23	0.26	0.30	0.32	0.39	0.32	0.34	0.43	0.32	0.38	0.49	0.28	0.34	0.39	0.42	0.25	0.28	0.21	0.26	0.25	0.24
10	0.21	0.27	0.29	0.22	0.25	0.29	0.31	0.38	0.32	0.33	0.42	0.31	0.37	0.49	0.27	0.34	0.38	0.41	0.24	0.27	0.20	0.25	0.23	0.23

Table 4 Quarterly results of multifractality

Time	Country	Hurst Average	Delta H	Delta Alpha	Fractal dimension(d)	LML	Ranking
Quarter 1	India	0.5043	0.5699	0.7229	1.4957	0.2850	6
	China	0.5081	0.4772	0.6410	1.4919	0.2386	4
	Japan	0.5374	0.5169	0.6816	1.4626	0.2585	5
	France	0.4624	0.4541	0.6161	1.5376	0.2271	3
	Spain	0.4784	0.4162	0.5692	1.5216	0.2081	2
	UK	0.4497	0.3042	0.4401	1.5503	0.1521	1
Quarter	India	0.5261	0.4297	0.5935	1.4739	0.2149	6
	China	0.5386	0.3140	0.4463	1.4614	0.1570	3
	Japan	0.5012	0.3224	0.4583	1.4988	0.1612	4
	France	0.5466	0.3933	0.5652	1.4534	0.1967	5
	Spain	0.5322	0.2876	0.4433	1.4678	0.1438	2
	UK	0.5410	0.2418	0.3804	1.4590	0.1209	1
Quarter 3	India	0.5140	0.2585	0.4007	1.4860	0.1293	3
	China	0.6044	0.2465	0.3878	1.3956	0.1233	1
	Japan	0.4929	0.4250	0.6113	1.5071	0.2125	6
	France	0.5212	0.3783	0.5295	1.4788	0.1892	5
	Spain	0.5444	0.2573	0.3869	1.4556	0.1287	2
	UK	0.4994	0.3497	0.4946	1.5006	0.1749	4
Quarter 4[a]	India	0.4620	0.4097	0.5780	1.5380	0.2049	4
	China	0.5296	0.5246	0.7019	1.4704	0.2623	6
	Japan	0.4373	0.3674	0.5541	1.5627	0.1837	1
	France	0.4903	0.3748	0.5404	1.5097	0.1874	2
	Spain	0.4971	0.4424	0.6375	1.5029	0.2212	5
	UK	0.4710	0.3850	0.5499	1.5290	0.1925	3

[a]Quarter 4 ranges from 01-Oct-2020 till 03-Dec-2020

(Δh) is observed for the Indian stock market, followed by the Japanese and Chinese markets with Δh of 0.57, 0.52 and 0.48 respectively. On the other hand, the lowest multifractality can be observed in the UK market, followed by Spain and France with Δh of 0.30, 0.42 and 0.45 respectively.

The results can also be confirmed using the width of the multiple spectrum $(\Delta \alpha)$ presented in Fig. 6. The Indian stock market remained least efficient in quarter 2 with the highest multifractality level $\Delta h = 0.43$ followed by France with Δh of 0.39. The United Kingdom market remained the least inefficient market exhibiting the lowest level of multifractality with Δh of 0.24 followed by Spain (Δh=0.29). The markets of China and Japan remained in the middle. The Chinese stock market shows great improvement while a significant decline in the market efficiency of the UK, France and Japan can be observed in quarter 3 of 2020. The Japanese stock market exhibits the highest multifractality (Δh=0.43), followed by France (Δh=0.38) and the UK (Δh=0.35). The Chinese stock market becomes the least inefficient market
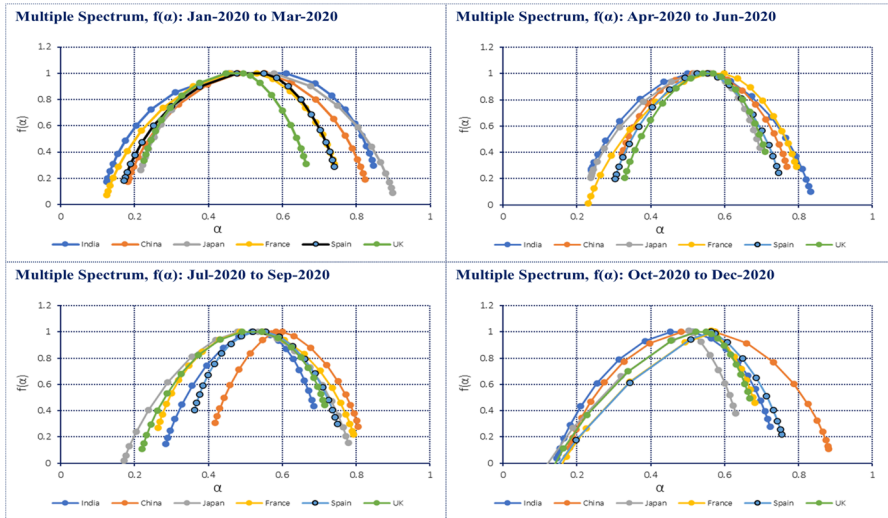
Fig. 6 Quarterly multifractal spectra for Asian and European stock markets

with the lowest multifractality level ($\Delta h=0.25$) followed by Spain and India with minimum variations. A mixed trend can be observed in the 4th quarter of 2020 with a decline in the efficiency of two Asian stock markets. The stock markets of China ($\Delta h=0.52$) and India ($\Delta h=0.41$) exhibit the highest multifractality while the markets of Japan ($\Delta h=0.37$) and France ($\Delta h=0.37$) become the least inefficient markets in the 4th quarter. For robustness, these results are supported by the LML inefficiency index calculated using Eq. 9 and reported in Table 4. A larger LML value indicates less efficiency of financial markets. For illustration purposes, in quarter 1, the Indian stock market shows the highest LML (least efficient) value of 0.28 while the lowest LML (least inefficient) is recorded in the UK.

According to National Securities Depository Limited (NSDL) data, Foreign Portfolio Investors (FPIs) did not resist to market pressure and withdrew a huge amount of 247.76 billion and 140.50 billion rupees from Indian equity and debt markets in only 13 days, from March 01, 2020 to March 13, 2020. Despite recent waivers by the Indian Government, the withdrawal of FPIs from the Indian economy remained, highlighting the danger of an uninsulated stock market in India. On the other hand, policies in the UK in the first and second quarters included, for example, the cut in bank interest rate from 0.75 to 0.25% at the beginning of March 2020 to provide liquidity and improve market efficiency. On March 19, 2020, the interest rate was cut again to 0.10%, this being the lowest interest rate in the 325 years of the bank's existence.

Interestingly, the results of the third and fourth quarters are in opposition. Japan is seen as the least efficient market in the third quarter but the least inefficient in the fourth one, while the Chinese stock market is seen to be the least inefficient in the third quarter but the least efficient in the next one. Japan has also allotted a rescue package of $992 billion to support the economy during this pandemic. This package

is nearly 20% of Japan's GDP, the largest package in the history of the country. It is intended to reduce the economic and social impact of Covid-19, targeting people, multinational companies, and small and medium-sized enterprises (SMEs).

3.3 Persistence level and herding behavior

Fernández-Martínez et al. (2017) suggest that the Hurst exponent of a time series is an authentic measure of herding behavior, and it was employed later by Mnif et al. (2019), when examining herding behavior in Islamic markets and by Mnif et al. (2020), when studying the herding behavior of cryptocurrency caused by Covid-19. The persistence of return series is an important determinant of multifractality.

According to the ranges, the results confirm that all Asian and European stock markets exhibit anti-persistent behavior (H < 0.5) with no detection of herding behavior in the first quarter of 2020. This means the markets systematically revert to the long-term mean and/or reverse themselves more consistently. However, a significant shift in the behavior of European stock markets can be observed in the 2nd quarter. All the European stock markets exhibited persistent behavior (H > 0.5), i.e., positive autocorrelation, with evidence of herding behavior, while there is no evidence of any herding behavior in the Asian stock markets during the 2nd quarter. The value of H > 0.5 indicates that traders intensify their herding behavior, evidence of positive feedback-based herding behavior in these stock markets.

In the second quarter of 2020, Europe became the epicenter of the global coronavirus pandemic and most European countries extended their restrictions and introduced lockdown. As a consequence of these measures, European markets recorded significant slumps and triggered sensitivity to asset losses, so they are more likely to display herding, and a wave of panic selling among investors is recorded in these stock markets.

The results confirm that the Spanish stock market had consistent persistent behavior with a trace of herding behavior after the 1st quarter of 2020. Overall, herding behavior in European markets is more evident than in Asian markets. Covid-19 has hit Spain harder than most countries in Europe in both human and economic terms, with infection rates far above other European countries. Spain's economic structure, with some dependence on activities like tourism led to severe economic damage due to the imposition of rules to reduce people's movements. These results are in line with other empirical findings such as in Espinosa-Méndez and Arias (2021) or Aslam et al. (2020d) and fit general expectations about the impact of Covid-19 cases and deaths on herding in financial markets.

3.4 DCCA correlation coefficient

In this section we analyze the DCCA correlation coefficient between the returns of the Chinese stock markets and the remaining indices, for all the quarters of 2020, with the results presented in Fig. 7. This shows that the connection of the different indices with the Chinese one was very high, during the first quarter of 2020, meaning that the turmoil caused by the health crisis passed to the
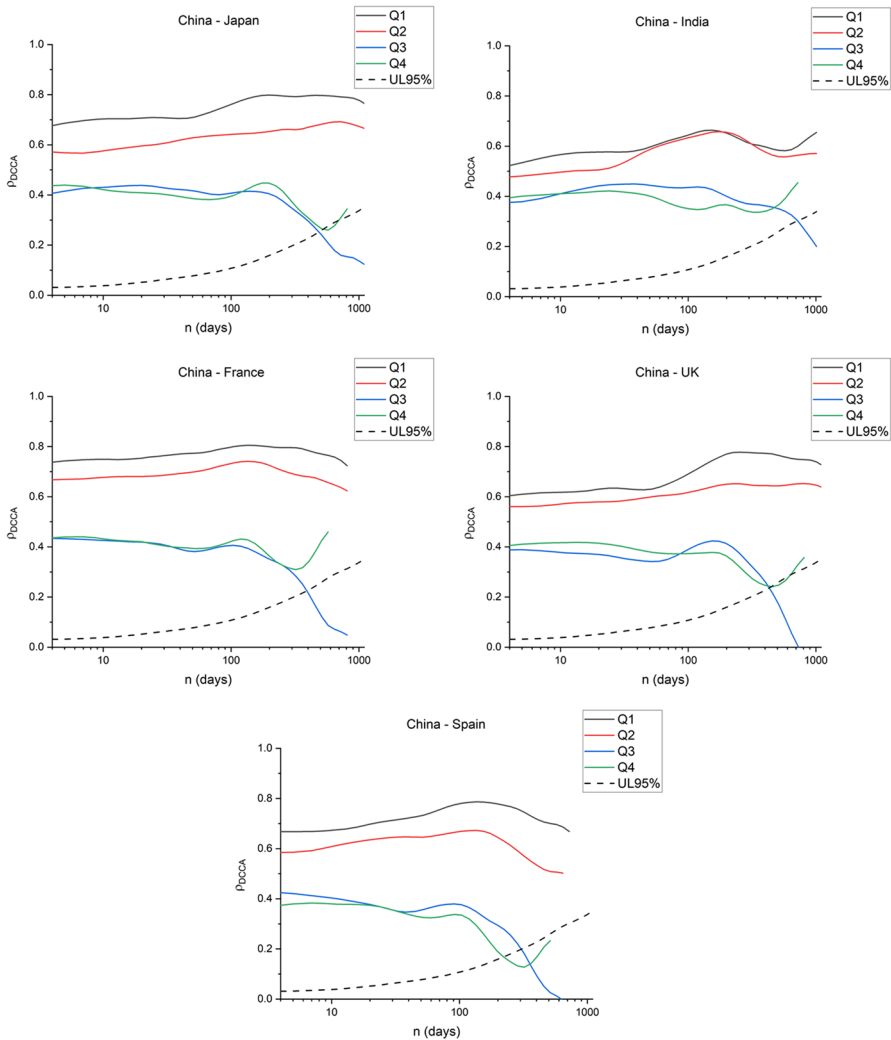
Fig. 7 Detrended cross-correlation analysis coefficient (ρ_{DCCA}) between the returns of Chinese stock market and the other stock markets, depending on n (time scales, in days). Dashed lines represent the upper critical values to test hypotheses H0: $\rho_{DCCA} = 0$ and H1: $\rho_{DCCA} \neq 0$

financial area, which is in line with Cepoi (2020) or Reinhart (2021) who found that dependencies between stock markets increased notably during the health crisis. After a critical moment at the beginning of 2020, which ended with Covid-19 being declared a pandemic in the middle of March, markets started to stabilize, and then the correlations of the indices with the Chinese one decreased, with Q2

levels, in general, above the correlations of Q1. For Q3 and Q4, the correlation levels are relatively similar, with some differences ocurring in Q4 but just for very high time scales, seeming to indicate that markets' connection with the Chinese one were mostly affected by the start of the health crisis.

4 Concluding remarks

Covid-19 has been destructive, not only regarding public health but also financial markets and economies in general, since it created unexpected levels of uncertainty and fear. Consequently, investors who are less informed try to imitate the behavior of those agents who are more informed, which leads to a psychological state of behavioral biases like herding. In this connection, this study provides an analysis of the dynamics of herding behavior during Covid-19 with respect to self-similarity intensity, long memory, and efficiency. The study used 15-min high-frequency data of Asian and European stock markets in India, China, Japan, the UK, France and Spain from January 01, 2020 to December 03, 2020. We employed the MFDFA proposed by Kantelhardt et al. (2002) along with the Generalized Hurst Exponent and Magnitude of Long Memory index as proposed by Khuntia and Pattanayak (2020), on a quarterly basis, to investigate herding behavior through multifractality, long memory and efficiency level.

Financial markets' efficiency is closely linked to their properties of multifractality, with our results confirming the presence of a multifractality pattern in all quarters but with different degrees. During the first two quarters, the least efficient market was India and the least inefficient market was the UK. The results of the third and fourth quarters are interesting and in opposition. While Japan is seen as the least efficient in the third quarter but less inefficient in the fourth quarter, the Chinese market shows the contrary evidence. Moreover, European markets are more sensitive to asset losses than Asian markets, so investors are more likely to show herding in European stock markets. Herding was at its peak during the 2nd quarter of 2020.

The results of this study clearly provide evidence about how Covid-19 has caused fear and anxiety among Asian and European investors, leading them toward herding behavior. Asian markets only show herding in the third quarter and it is also clear that the third wave of Covid-19 affected Asian countries more. European countries are greatly affected by the first and second waves of Covid-19, compared to Asia, and herding behavior can also be seen in the second quarter. However, Spain is the most affected country in Europe and herding behavior is evident in all quarters except for the first, which is in line with the results of Aslam et al. (2020e).

The presence of significant herding behavior during Covid-19 is documented in this study and confirms the presence of high multifractal patterns that lead to market inefficiency during this pandemic. The herd instinct is a significant driver of

asset bubbles in financial markets and could give rise to potentially destabilizing outcomes, although as reported in the literature review it could be driven by rational choices by speculators who have short horizons, arbitrageurs or noise traders. This could affect informational efficiency and create irrational bubbles, which could culminate in achieving higher returns, as speculators might tend to focus on a single information base rather than employing different sources of information. Moreover, the more investors get this information, the more disseminated it will be in the market, and so it is useful if they obtain it early. Therefore, it should be closely monitored. These findings provide useful insights for foreign institutional investors, traders and policy-makers. Moreover, significant herding in Europe also suggests that regulatory measures like enhancing transparency and investor trust must be adopted to improve the quality of the informational environment and highlight the importance of the economy. As a result, this could make markets more attractive to international investors and also increase trade.

5 Availability of data

The data presented in this study are available on request from the corresponding author.
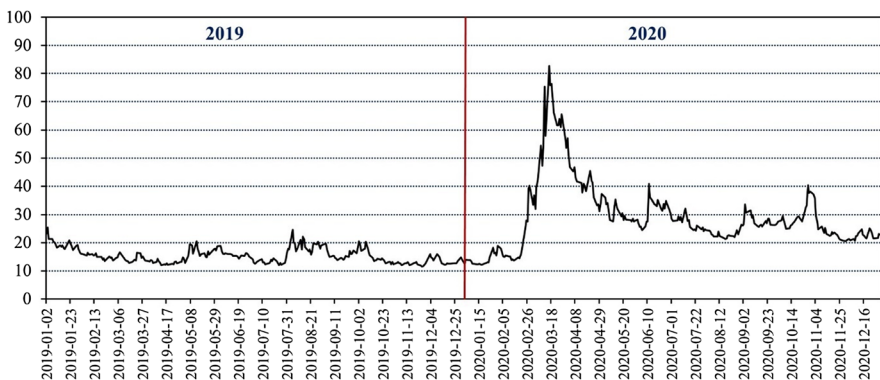
Appendix A

See Fig. 8

Fig. 8 Daily cosing values of VIX index. Source: Author's own calculations

Code availability The codes used in this study are available on request from the corresponding author.

Declarations

Conflict of interest The authors declare no conflict of interest.

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