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ORIGINAL ARTICLE

Herd investing and market inefficiency in forex markets over the COVID-19 outbreak: the multifractality analysis

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Abstract

This study investigates how the coronavirus pandemic influenced the 5-day-week multifractal characteristics of top five foreign exchange rates - USD/EUR, USD/GBP, CNY/USD, JPY/USD, and CHF/USD - using weekday index data covering the period from 2 January 2018 to 20 July 2022. The major objective is to determine whether herd investing behavior and the degree of market inefficiency changed between the pre-first-lockdown period (2 January 2018–22 March 2020) and the post-first-lockdown period (23 March 2020–20 July 2022). The generalized Hurst exponents are estimated using the multifractal detrended fluctuation analysis (MFDFA). The empirical findings indicate that multifractality is present in each of the examined exchange rates during the COVID-19 outbreak. Moreover, the degree of market inefficiency varies across the selected spot rates. The results further suggest that the post-first-lockdown period was more prone to herd investing for USD/EUR, USD/GBP, and CHF/USD. In addition, based on the MLM (inefficiency) index, empirical evidence reveals that USD/EUR and CHF/USD became more vulnerable in the post-first-lockdown period. Considering the impacts of this far-reaching global shock, the highest MLM (inefficiency) index value is associated with CNY/USD before the first lockdown and with USD/EUR after the first lockdown.

Keywords Foreign exchange market · Multifractal detrended fluctuation analysis · MLM (inefficiency) index · Herding behavior · COVID-19 pandemic

JEL classifications C1 · G1 · G14

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Introduction

The global financial relations and transactions have triggered the spread of economic shocks in recent years, along with aggravating the rise of market disorders and anomalies. In particular, the fields of studies to analyze the degree of market efficiency and its potential determinants gain attention for the research topics through covering the socio-economic impacts of the COVID-19 pandemic on financial sector to a large extent. It is kind of a matter of curiosity for whether there is a change in the risk-based buying and selling decisions of market participants and how it is reflected in different markets. For instance, as one of the critical tendencies of both real and financial investors, herd investing has become a trend topic more recently for examining the financial bubbles and explosive behaviors among the economic actors where it is commonly used to refer that the behavior of market players can be suppressed by the others in their investment decisions together with a decrease in confidence and an increase in uncertainty for future strategies.

To provide a suitable basis for understanding the market vulnerabilities, the structural changes can be taken as the primary way to evaluate the shifts in financial transactions during the coronavirus disease. For instance, unlike the previous crises, the financial preferences of investors have mostly tended towards alternative markets to be invested during the COVID-19 outbreak such as cryptocurrencies. One of the ample reasons that incline investors to buy and sell crypto assets depends on the fact that transactions take place very quickly and they are usually considered as safe haven within the scope of whole advantages of blockchain technology where they are exposed to decentralized exchanges. On the other hand, however, the movements of different digital assets' prices are also characterized by suspicious findings regarding the reliability of those assets (Conlon and McGee 2020). Therefore, uncertainties in the financial system make it difficult to predict how the potential impacts of macro variables can alter the market structures. Regarding that point, this study is based on the empirical investigation of the existence of herd investing and the degree of market efficiency in selected foreign exchange (forex) markets during the COVID-19 outbreak. Although there are a bulk of studies in relevant literature covering the changes in the markets for stocks and digital assets, empirical investigations towards herd investing and the degree of market inefficiency in foreign exchange markets are rare. Therefore, this study aims to explain the reactions of exchange rates to herd investing and to assess the forex market stability for the pre- and post-COVID-19 periods.

Thereafter the first case that emerged in Wuhan, China in December 2019, the virus rapidly spread all over the world and turned into a global pandemic along with the shocks that destabilized the real and financial markets. As of March 2020, when the pandemic started to spread all over the world, growth expectations were negatively affected and most countries had to take measures that they had never been applied before. The long quarantine periods with other measures taken by governments have significantly restricted economic activities and left alone the economic units in a vulnerable position by causing a decrease in global mobility, contraction of production and consumption channels, disruption of trade and supply chains (OECD 2020). As a matter of fact, in the IMF World Economic Outlook Report dated January 2022, it was noted that the global economy will enter 2022 in a weaker position than expected.

As depending to past experiences with financial shocks, unexpected events in a market system may lead to multi-pronged asymmetrical movement patterns in terms of the level of market efficiency. Moreover, while the negative impacts of the 2007/2008 global crisis on economic units have not been completely resolved yet, the COVID-19 pandemic has led the ongoing problems in markets (especially in financial markets) to deepen. However, the fact that the pandemic covers a long period in which it results in the disruptions of economic transactions to increase further and leads to market resistance being broken. Within the framework of these dynamics, the markets are faced with a major deterioration by involving an aggressive revaluation process (Aslam et al. 2020a).

The remainder of this study is structured as follows: Sect. "Literature Review" is based on the literature review. Section "Data and Methodology" describes the data and the methodology. Section "Empirical Findings" summarizes the empirical findings based on MFDFA. The last section concludes.

Literature review

The ongoing degradation of core macro- and micro-based indicators during the pandemic period has further increased the level of uncertainty in economic transactions and brought about a sudden shakeout in the prices of assets (Ayittey et al. 2020). In that vein, investors have been confronted with serious losses due to sharp falls in asset prices (OECD 2020; Contessi and de Pace 2021). The fact that sharp losses were felt especially in stock markets by raising the level of uncertainty among various financial investors. In such an environment, the investment preferences of financial market participants have turned to risky investments that promise higher rates of return to reduce their excessive losses. Hence, most of the economic units have moved away from traditional (risk-free) investment approaches and have tended more to speculative assets along with the emergence of potential anomalies in relevant markets.

Following the recent patterns in financial transactions and the relevant weaknesses in financial movements, it can be deduced that a bulk of studies have revived their attention to focus on detecting volatility spillovers, bubble behavior, and contagion effects to assess whether the financial markets are inherently stable. For instance, many of those studies have focused on the impact of novel coronavirus outbreak to reveal the changes in different types of markets where the price system substantially collapsed over a wide range of countries (Ashraf 2020; Goodell 2020; Liu et al. 2020a; Sharma 2020; Yan 2020; Takahashi and Yamada 2021). Besides, a large part of researchers took action to examine stock movements and to detect volatility and explosive bubbles in asset prices (Phillips et al. 2011, 2015; Bettendorf and Chen 2013; Hu and Oxley 2017; Phillips and Shi 2018, 2020). The most common argument grounded on the fact that market shocks, especially in financial crises, greatly lead to an increase in volatility and explosive bubbles along with exacerbating financial instability. Within this scope, the general perception tends to assume that the COVID-19 outbreak has increased volatility in financial markets mostly due to an increase in the level of uncertainty among financial investors (Alber 2020; Baker et al. 2020; Lee and Chen 2020; Narayan 2020; Ramelli and Wagner 2020; Salisu et al. 2020; Sansa 2020; Sha and Sharma 2020; Zaremba et al. 2020; Zhang et al. 2020; Albulescu 2021; Ashraf 2021; Mazur et al. 2021).

According to Baker et al. (2020), the COVID-19 outbreak was one of the harsh experiments in financial transactions throughout the historical process of other health diseases since it caused one of the biggest volatilities in several stock markets. Examining the effects of the COVID-19 pandemic on the Chinese stock market, Yan (2020) states that investors' behavior was adversely affected by the sudden drop in stock prices at the outset of the coronavirus pandemic. In a similar vein, Ramelli and Wagner (2020) and Zaremba et al. (2020) confirm that the coronavirus pandemic has been negatively influential on stock market returns and volatility. Besides, Mazur et al. (2021) find that there was an asymmetric volatility for the firms operating in S&P Composite 1500 and an inverse linkage between the returns of stocks and volatility. Basuony et al. (2021) analyze the effects of stock indices of nine countries where the cases of coronavirus disease were most intense on stock market behavior through the exponential general autoregressive conditional heteroskedastic (EGARCH) model. According to the empirical findings extracted by the EGARCH method, the negative impact of the pandemic on stock markets has been confirmed for the selected sample of nine countries. This negative effect also triggered an increase in the bad state probability and conditional volatility of stock markets. Akhtaruzzaman et al. (2021) also investigate financial contagion effect of the coronavirus pandemic and find that the correlation between the stock returns of China and the G7 countries strengthened during the latest pandemic which then resulted in the spread of financial contagion among those countries.

Furthermore, Sharma et al. (2021) state that COVID-19 cases have significant effects on exchange rates and stock returns in the long run towards the use of wavelet coherence method. Along with the implementation of the same method, Choi (2020) finds that the raising level of economic uncertainty during the COVID-19 outbreak affected the degree of volatility in S&P500 more than the global financial crisis of 2007–2008. However, there are also counterarguments in which they are based on the findings that most of the firms/investors have turned the negative impacts of the current crisis environment into an opportunity during the COVID-19 pandemic. Mazur et al. (2021), for instance, imply that stock prices have sharply felt in most sectors throughout the COVID-19 outbreak, but some sectors had a chance to turn positive of ruined financial statements through implementing government policies as a trigger for changes in stock prices and the effects of price volatility. Narayan (2020) also investigates the explosive bubble behavior during the coronavirus pandemic to assess whether the foreign exchange markets are efficient in terms of the following four currencies: Euro, Sterling, Canadian Dollar, and Japanese Yen. His findings suggest that the explosive bubble behavior has strengthened during the coronavirus pandemic, pointing to an increase in the degree of market inefficiency. In such a situation, deviations from the equilibrium price act as a signal that triggers the factors leading to market inefficiency. When financial investors are convinced of market inefficiency, they may adopt the strategy of moving away from that market.

One of the highlights of market efficiency in crisis-prone periods is the increase in the predictability of the return of financial assets (Cujean and Hasler 2017; Baker et al. 2020; Liu et al. 2020b). On the one hand, crises cause an increase in risky behavior; on the other hand, they can create new investment opportunities by increasing the predictability of the return on financial assets. In this direction, the expansionary monetary policy implemented by the FED to suppress the COVID-19 outbreak might have encouraged market participants to search for profitability in the financial markets (Hong et al. 2021). In particular, the unexpected change in money supply can lead to an excessive increase in the exchange rate since consumer prices cannot immediately adapt to that change in money supply (Dornbush, 1976). Although financial investors have substantially responded quickly in the forex markets during the COVID-19 outbreak, government interventions have followed the way to fix the deterioration in currencies with delay, especially in developing and emerging economies. In line with these conditions, the financial markets were increasingly dragged into a higher level of inefficiency. According to Aslam et al. (2020a), the effect of COVID-19 on forex markets, however, might differ through the implementation of proper government policies, binding the market position of currencies, and analyzing the risk sensitivities.

Related to the mitigating role of government during the coronavirus pandemic, Narayan et al. (2021) reveal that proactive government policies in G7 countries had led to occurrence of positive effects on stock markets. In support of Narayan et al.'s (2021) findings, Ma et al. (2020) notice that countries with more intense fiscal policies were relatively more successful than the other policies to reduce the potential devastation effects of the coronavirus pandemic on economic growth. Meanwhile, other studies dealt with the effects of the relationship between social trust and investor movements on financial markets (Adams 2021; Engelhardt et al. 2020, 2021). For example, Engelhardt et al. (2020) remark that the degree of volatility is highly correlated to the perception of trust in the market, and that volatility is located at lower levels in economies where social trust is relatively high.

In addition to the aforementioned factors, the current news about the coronavirus pandemic reflects the changes in market perception and thereby the investors' behavior. According to Dzielinski (2011), the bad-news bias lowers the market returns below the average. In particular, all news and updates on economic crises that motivate the world's agenda can lead to a potential increase in the future anxiety of economic actors by affecting investor decisions (Tetlock 2007) and thus a reduction in market returns and higher volatility (Cepoi 2020; Haroon and Rizvi 2020; Tan 2021). In that vein, Cepoi (2020) states that pandemic news has an asymmetric effect on stock markets. Consistently, Tan (2021) argues that there is an asymmetric dependence between the news about the pandemic and the financial market returns. Furthermore, Basuony et al. (2021) refer that the negative effects of pandemic-related death rates on stock prices are more dominant than the positive effects of the recovery rates. Ambros et al. (2021) also gain attention to the dynamics that are decisive in taking action regarding the financial markets where the bad news about the coronavirus pandemic has potentially been effective for the increase of stock market volatility in European economies.

Considering the volatility trends and explosive bubbles in exchange rates during the coronavirus pandemic, the concept of market efficiency comes to the fore to examine the functioning of financial markets and to find new strategies (Dotsika and Watkins 2017). For that consideration, the Efficient Market Hypothesis (EMH) leads to indicate that the market prices contain full information where the economic units take their economic decisions in a way that provides an optimum benefit over the equilibrium price. Assuming that market actors are rational, it is widely accepted that all information in the market is instantly reflected in prices (Fama 1965, 1991; Samuelson 1965). Therefore, investors do not have a chance to reach opportunities for extra profits (Rapp and Sharma 1999) where prices are indeed random and future asset prices are not predictable (Iwatsubo and Kitamura 2009). At the same time, considering market efficiency, investors are not supposed to have excess returns from speculative motives (MacDonald and Taylor 1992). However, in contrast to that theoretical perception, Hong et al. (2021) investigate the predictability of stock return for the United States and find that it has been compounded by the price volatility over the COVID-19 outbreak which triggered the speculative behaviors, profit opportunities, and market inefficiency. Besides, the findings from Hong et al.'s (2021) study reveal that the coronavirus pandemic strengthened the current inequality level in the financial sector due to the reason in which those who extracted most of the profitable investment opportunities were the investors with abundant funds.

Meanwhile, the analytical investigation of efficiency level in forex markets is based on the assumption that the prices reflect all the necessary information for the investors (Dowla 1995). Under the weak form of efficiency assumption, the current exchange rate reflects all information from the past (Kühl 2007). In the semi-strong form, exchange rates are mutually supported by full information in which they convey among each other through the market mechanism. Therefore, investors cannot use historical prices and public information to obtain extraordinary profits in the forex market (Mehrara and Oryare 2012). However, according to Grossman and Stiglitz (1980), the prices are partially allowed to be formed in the market and thus reflect certain information for the investors. Besides, Sewell (2011) points out that investors are inclined to make more transactions to obtain a higher level of information, and hence they deal with the issue of how more income can be generated in the market system to cover the cost of information where the marginal profits of individual and institutional investors exceed their marginal costs (Bernstein 1999).

The predictability of the rate of return in foreign exchange markets for a weak form of market efficiency has been analyzed by various studies (Chiang et al. 2010; Abounoori et al. 2012; Lazăr et al. 2012; Iyke 2019, 2020). Iyke (2019) examines the forex market efficiency in Indonesia by using the GARCH model and implies that a weak form of efficiency is empirically robust in the short term whereas the predictability of returns due to the forex market inefficiency in a small number of currencies will make it possible to obtain positive rate of profit. Lazăr et al. (2012) emphasize that the global crisis had a negative impact on money market efficiency in most of Central and Eastern Europe (CEE) by approaching the generalized spectral method in a rolling window and note that Poland, Romania, and Hungary regained market efficiency in the later phase of the financial shocks. Abounoori et al. (2012) use the detrended fluctuation analysis (DFA) technique to test the market efficiency in terms of the Rial/US Dollar exchange rate for the 2005–2010 period and show that the Iranian foreign exchange market has a weak form of inefficiency. Iyke (2020) also suggests that exchange rates can be predicted during the coronavirus pandemic and thus they reflect all publicly available information. If the foreign exchange market is efficient in nature, the current forward rate should be an unbiased estimator of the future spot rate (Rapp and Sharma 1999). According to Wong and Ahmad (2013), for instance, the forward exchange rate can be assumed as an unbiased estimator of the spot exchange rate within the European economies in which the forex market is characterized by pricing efficiency. On the other hand, Mehrara and Oryare (2012) point out that the market efficiency was only binding for the pre-crisis period of 2007/2008.

The global increase in uncertainty levels and the destruction of confidence can be depicted as the key determinants of potential shifts in investor trends and behavior. The fact that investors are mutually linked to the behaviors of other market players when they are faced with an excess degree of uncertainty in the presence of publicly available information and thus strengthen the common motives towards herd investing (Banerjee 1992). Particularly in the case of a higher uncertainty level of markets triggered by financial shocks, investors may tend to rely on the decisions of others by mostly following the return of their financial assets and ignore their instant level of information about the markets. Hence, herd investing is triggered by a disruptive effect on market volatility as well as financial contagion, and speculation (Chiang and Zheng 2010; Mobarek et al. 2014; Filip et al. 2015; Fang et al. 2021).

For instance, Chiang and Zheng (2010) investigate the link between the financial crisis of 2007–2008 and herd behavior for the stock markets of 18 selected countries and find that the immediate crisis posed by the financial meltdown in 2007–2008 exacerbated herd mentality bias in the origin country and spread the contagion effect to the other countries where investors follow and copy what they perceive of other investors are doing rather than their own analysis. Mobarek et al. (2014) also discuss the presence of herd behavior in terms of European economies. The empirical findings refer that there was a strong increase in herd behavior during the crisis period with a varying degree for each country where it was more pronounced in Scandinavian countries during the Eurozone crisis but the others such as Portugal, Ireland, Italy, Greece, and Spain (PIIGS countries) were affected in whole period. Meanwhile, Filip et al. (2015) find that stock prices are inherently fluctuated over time since investors mostly opt for the most suitable assets and investment opportunities where the other individual investors may follow the same strategies turned out with the speculative bubbles in the Central and Eastern Europe (CEE) stock markets.

Apart from traditional investment preferences, and the increasing demand for digital currencies in recent years, there is also a growing interest in studies to understand the investor behavior in cryptocurrency markets. Da Silva et al. (2019) and Fang et al. (2021) use the modified Cross-Sectional Absolute Deviation (CSAD) approach to imply that herding bias is currently active in digital asset market where the existence of contagion effect is highly relevant in times of crisis consolidated by the shifting away of investors from Bitcoin to safer financial assets. Similar conclusions are consistently supported by other studies investigating the herd behavior in financial markets over the COVID-19 pandemic. For instance, Wu et al. (2020) find that herd behavior was lower than usual in Chinese stock markets during the coronavirus pandemic and hence the stock markets were relatively more efficient than the previous periods. Using the daily closing prices of 191 companies in the Indian stock market for the period between January 1, 2015 and June 1, 2020, Dhall and Singh (2020) indicate that there was an absence of herd formation over the 1 January 2015–1 June 2020 period and pre-COVID-19 outbreak whereas herd behavior spread among the individual investors over the post-COVID-19 outbreak (1 January 2020–1 June 2020).

The mainstream wisdom assumes that stock prices are normally distributed which together supports the random walk hypothesis (RWH) (Bachelier 1900). In consideration of RWH, Worthington and Higgs (2006) apply serial correlation coefficient to examine random walk in selected 15 Asian economies and find that there is no evidence of random-walk behavior of stock prices in emerging markets by pointing out the weak form of efficiency. Claessens et al. (1995) test the return anomalies and predictability for stock markets of 20 emerging economies which were characterized by inefficiency. Chiang et al. (2010) provide strong evidence that random walk models of exchange rate return series cannot be rejected and have a weak form of efficiency in Japan, South Korea, and the Philippines whereas Taiwan's exchange rate is inefficient.

However, more recent studies reject the RWH hypothesis and argue that asset prices have various principal determinants (Mandelbrot 1967, 1975, 1997) which cover fat tail (Gopikrishnan et al. 2001), volatility clustering (Jacobsen and Dannenburg 2003; Cont 2007), fractals and multifractals (Di Matteo et al. 2005; Su et al. 2009; Zunino et al. 2009), and chaos (Adrangi et al. 2001). In particular, fractal and multifractal procedures have been widely accepted in financial market analysis. Using Rescaled Range (R/S) analysis, Peters (1991, 1994) made monofractal features meaningful in several financial markets. However, the lack of this analysis based on monofractal properties is that it cannot qualify the following procedures: (i) multifractal height cross-correlation analysis (Kristoufek 2011), (ii) multifractal detrended fluctuation analysis (MFDFA) (Kantelhardt et al. 2002), and (iii) partition function method (Yuan et al. 2009).

As one of the recently used techniques, the MFDFA is implemented in the relevant literature to detect stock market asymmetry, which was formerly examined with Detrended Fluctuation Analysis (DFA) (Peng et al. 1994) to avoid the spurious detection of long-range dependence in non-stationary data. The DFA is then generalized by the MFDFA (Kantelhardt et al. 2002) to explore multifractality in time series data. This method of analysis is used to determine multi-connected structures of financial time series (Rizvi et al. 2014; Aslam et al. 2022) indicating possible market inefficiency (Zunino et al. 2008; Lee et al. 2017, 2020; Tiwari et al. 2019). For instance, Rizvi and Arshad (2016) investigate the shifts in speculative movements, volatility, and market efficiency for Asian markets by employing MFDFA method to provide an opportunity to compare sample countries along with their historical experiences and find that the 2007–2008 global crisis had different impacts on several countries, whereas the negative effects of the 1997 Asian Crisis on East Asian countries were also presented.

Additionally, it can be pointed out that the efficiency in foreign exchange markets changes during the time of economic downturns (Levich et al. 2019) and thus leads to a higher rate of market anomalies (Li and Miller 2015). In consideration of that change, Aslam et al. (2020a) consider six currencies in the initial stage of the COVID-19 outbreak through the MFDFA method where the empirical outputs present that there has been a harsh decrease in the degree of market efficiency due to the slowdown in financial transactions and a sharp fall in asset prices. Moreover, the given findings showed that there was a significant change in the strength of multifractality along with a fall in the degree of the forex market efficiency and a substantial change in investors' strategies. Using a sample of four major currencies and employing the MFDFA procedure, Shahzad et al. (2018) report that the efficiencies of the British Pound and Euro were getting lower to a large extent, while the Japanese Yen and Swiss Franc became more efficient over time. Similarly, Han et al. (2019) found similar results by employing the MFDFA procedure and confirmed that the Japanese Yen had the lowest multifractal feature and were the most efficient exchange rate in contrast to EUR, GBP, and CAD over the 2005–2019 although both of them confronted with multifractality. Besides, Ning et al. (2018) show that the British Pound and the Euro had also nonlinear multifractal structure for the same time horizon.

MFDFA also allows for testing the asymmetrical connections among different stock markets (Lee et al. 2017; Arshad et al. 2019; Miloş et al. 2020). For instance, Lee et al. (2017) document that the US stock indices showed multifractal features due to the asymmetric framework. Miloş et al. (2020) also refer to the existence of long-term correlations in the returns of stock indices in seven Central and Eastern European (CEE) countries, implying that the market inefficiency was highly significant. On the other hand, Arshad et al. (2019) state that emerging Asian stock markets had much more stability and efficiency in the long term, whereas the financial fragilities had a short-term negative impact on the productivity of emerging markets.

All in all, this study uses daily data of selected five exchange rates, namely USD/EUR, USD/GBP, CNY/USD, JPY/USD, and CHF/USD, from the date of 2 January 2018 to 20 July 2022. Multifractal detrended fluctuation analysis (MFDFA) proposed by Kantelhardt et al. (2002) is used to determine whether the selected exchange rates face a higher level of multifractality and inefficiency during the COVID-19 outbreak. The MFDFA approach provides the opportunity to detect the movements in the selected exchange rates and the extent of market risk. It allows individual and institutional investors to monitor the current market structure. The major reason to employ the MFDFA on selected foreign exchange rates is to cover different algorithmic toolboxes for forecasting financial risks and potential downturns in financial markets and to characterize the variability and uncertainty in financial time series, which is diverged from the Gaussian-based distribution models. Further, we examine the pre-pandemic period and post-pandemic period separately to allow comparison of the changing dynamics of exchange rates.

Data and methodology

Data description

The data is collected through daily trading of foreign exchange rates obtained from the Board of Governors of the Federal Reserve System. The selected exchange rates are as follows: (i) U.S. Dollars per Euro (USD/EUR), (ii) U.S. Dollars per Pound Sterling (USD/GBP), (iii) Yuan Renminbi per U.S. Dollars (CNY/USD), (iv) Yen per U.S. Dollars (JPY/USD), and (v) Swiss Franc per U.S. Dollars (CHF/USD) from the date of 2 January 2018 to 20 July 2022. The whole sample is divided into two stages covering as before the first lockdown is announced in the world (which is chosen as an average date across the globe) and after the first lockdown period. On the one hand, the average date for the first lockdown corresponds to the date 23 March 2020. On the other hand, the second period includes the dates right after the first lockdown is announced till 20 July 2022. In this regard, the daily sample is used to assess the post-performance of selected exchange rates at the coronavirus outbreak based on the lockdown effects. Table 1 presents the list of selected exchange rates and the summary statistics for each period.

Methodology

The steps for the analysis of daily fluctuations in selected foreign exchange rates are divided into three parts[1].

Table 1 Summary statistics

Foreign Exchange Rates	Period	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis
USD/EUR	Before	1.1457	1.2488	1.0682	0.0422	0.9142	2.9012
	After	1.1502	1.2295	1.0028	0.0521	-0.6074	2.4733
	Total	1.1480	1.2488	1.0028	0.0475	-0.0643	2.5737
USD/GBP	Before	1.3044	1.4332	1.1492	0.0505	0.3934	3.2698
	After	1.3246	1.4188	1.1763	0.0594	-0.4557	2.1127
	Total	1.3147	1.4332	1.1492	0.0561	-0.0517	2.2901
CNY/USD	Before	6.7796	7.1786	6.2649	0.2539	-0.7203	2.3310
	After	6.6076	7.1681	6.3084	0.2471	0.8605	2.3737
	Total	6.6918	7.1786	6.2649	0.2649	0.0714	1.5945
JPY/USD	Before	109.62	114.19	102.52	2.1004	-0.1046	2.5622
	After	111.94	138.94	102.71	8.1884	1.5907	4.7833
	Total	110.81	138.94	102.52	6.1404	2.3906	9.3491
CHF/USD	Before	0.9842	1.0218	0.9232	0.0191	-0.9810	3.6419
	After	0.9274	1.0028	0.8784	0.0259	0.7379	2.9703
	Total	0.9552	1.0218	0.8784	0.0365	-0.1821	1.6739

"Before" and "After" show the statistics for the data covering the pre-first-lockdown and post-first-lockdown periods, respectively. "Total" indicates the whole sample period

[1] The primary article on which the methods used in the present study are based is the work of Özdemir and Kumar (2024).

Step 1: the measurement of logarithmic fluctuations

As a first step, given the time series of exchange rates $\epsilon_0, \epsilon_1, \ldots, \epsilon_{N+1}$, the logarithmic fluctuations are defined as:

$$r_i\left(t\right) = log\left(\frac{\epsilon_t}{\epsilon_{t-1}}\right) \tag{1}$$

where $r_i\left(t\right)$ is the change/fluctuation in exchange rates and ϵ_t is the spot rate at date t. The selected exchange rates exhibit different patterns than the rest of the others during the coronavirus outbreak as depicted in Figures (1, 2, 3, 4, 5). In this regard, one can present some spot rates as risk-free and potential hedges compared to holding in domestic currency whereas the opponents may support the argument that those assets are poor hedges and thus provide outstanding gains to individuals and institutions along with a signal for an upward swing in the degree of uncertainty and herd investing.

Step 2: seasonal and trend decomposition using loess (STL)

Just before the application of MFDFA to the selected exchange rates, the empirical framework is based on employing the Seasonal and Trend Decomposition using Loess (STL) method, initiated by Cleveland et al. (1990), to decompose the series in

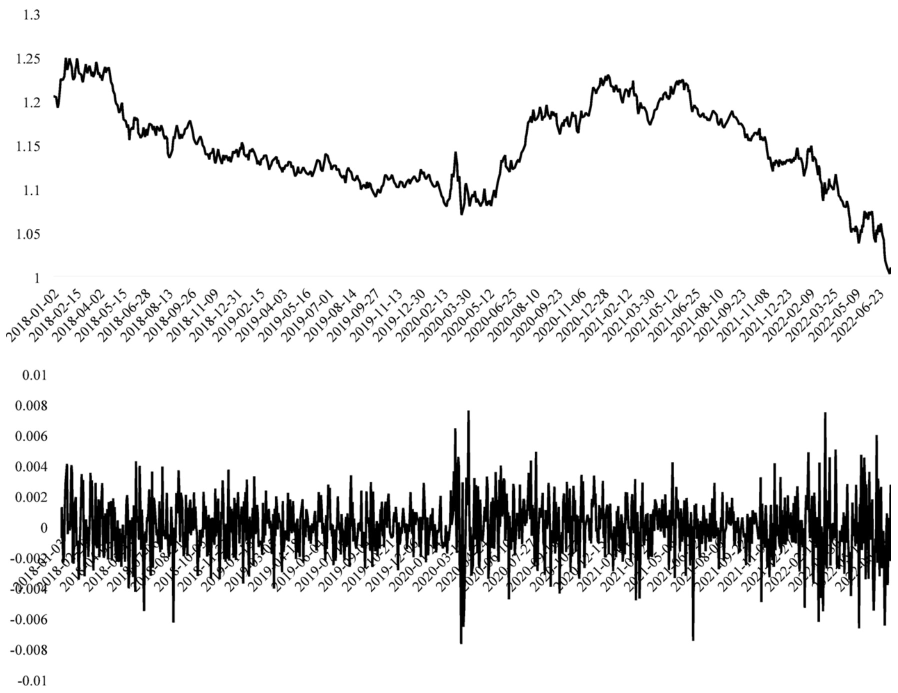

Fig. 1 USD/EUR daily trend and fluctuations

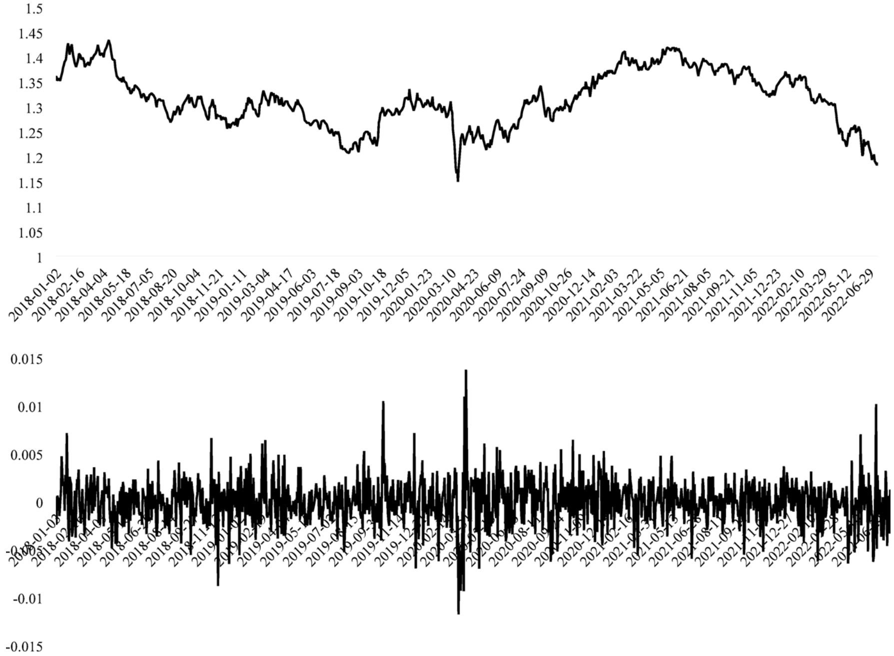

Fig. 2 USD/GBP daily trend and fluctuations

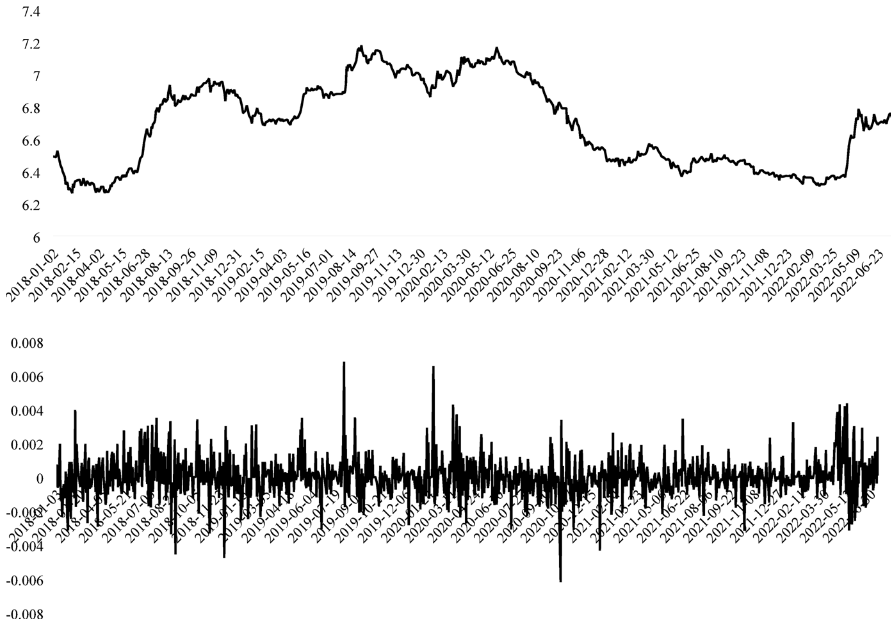

Fig. 3 CNY/USD daily trend and fluctuations

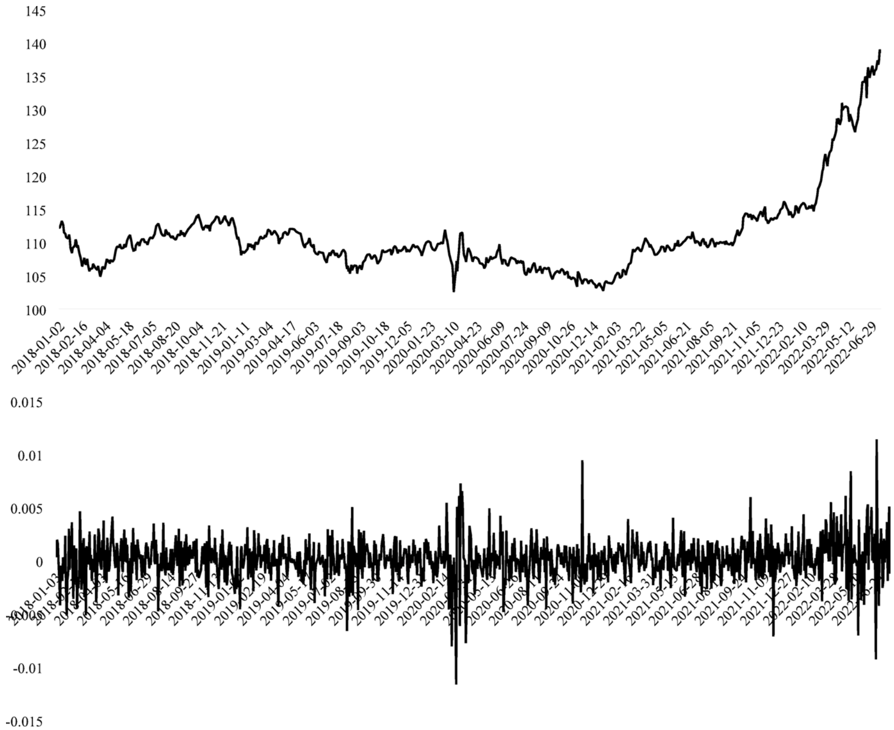

Fig. 4 JPY/USD daily trend and fluctuations

which the nonlinear correlations are measured with various components. The STL is regarded as a robust method of time series decomposition done for locally fitted regression models to decompose the series into trend, seasonal, and remainder components. In this regard, it can be used for any dataset. However, remarkable feedback from the selected data is generally obtained if recurring temporal patterns are found in given series such as the daily fluctuations in foreign exchange rates. The pattern performs the outcomes from the STL method as the seasonal component.

The STL algorithm has a smooth process on the selected time series carrying out Loess in inner and outer loops. On the one hand, the inner loop iterates between seasonal and trend smoothing. On the other hand, the outer loop minimizes the outlier's effect. Meanwhile, the seasonal component is primarily measured at the inner loop and then adjusted to calculate the trend component. The remainder is the difference between seasonal and trend components.

The daily fluctuations series for selected foreign exchange rates are decomposed into deterministic and stochastic components using the Loess smoother (Cleveland et al. 1990). The STL method classifies each series as three different components: trend (T_i), seasonal (S_i), and the stochastic remainder (R_i) (Laib et al. 2018a, b; Miloş et al. 2020). Considering the daily fluctuations in exchange rate series, the mentioned-above components of the STL method can be depicted as follows:

$$\gamma_i(t) = T_i + S_i + R_i \tag{2}$$

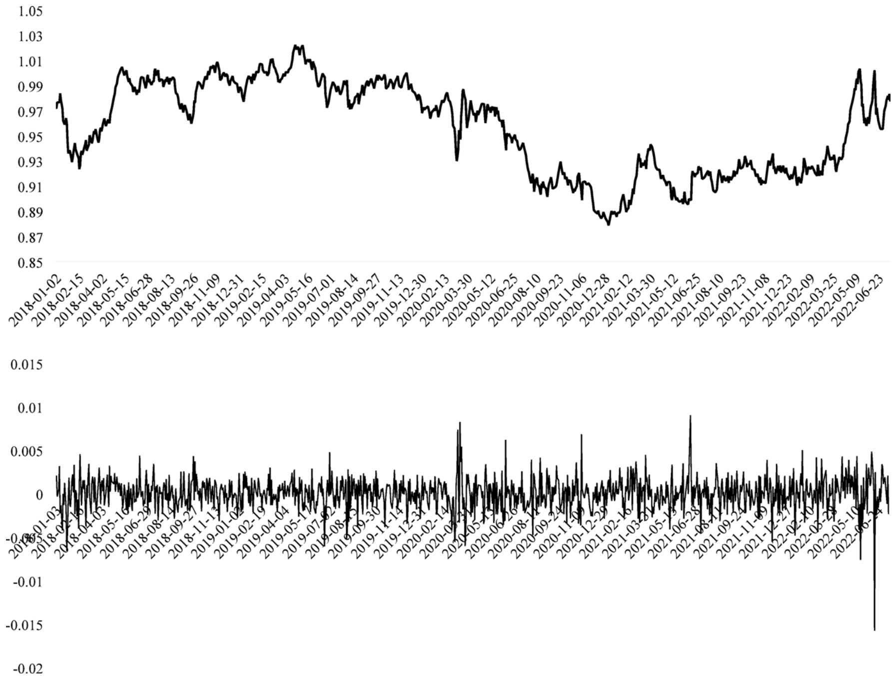

Fig. 5 CHF/USD daily trend and fluctuations. *Source*: Board of Governors of the Federal Reserve System

where γ_i stands for the daily fluctuations of exchange rate series based on a logarithmic scale, T_i is the value of the trend component, S_i is the value of the seasonal component, and R_i is the value of the remainder component at point i. To decompose the series, the Rstudio package "STL" is used to perform STL decomposition (Cleveland et al. 1990; Laib et al. 2018a; Aslam et al. 2020a; Miloş et al. 2020). In a daily fluctuation of the series, the span of the Loess window for seasonal extraction is determined as 30, which covers each day of spot rates in one month.

Figures (6, 7, 8, 9 , 10) represent the STL decomposition of fluctuations in selected spot rates. In other words, each graph corresponds to the current daily fluctuations occurring in selected currency prices in the forex market with the trend, seasonal, and remainder components.

Step 3: multifractal detrended fluctuation analysis (MFDFA)

The main empirical interest of this study is to employ the multifractal detrended fluctuation analysis (MFDFA) to form an estimate of whether the selected spot rate series are multifractal. Regarding the MFDFA method, the empirical strategy is based on two distinctive analyses, covering the generalized Hurst exponent (GHE) and the magnitude of long-memory (MLM), to detect the possibility of bubble explosion in spot rate series throughout the detection of market inefficiency and thereby the herd investing behavior. To determine the presence of those kinds of issues, the empirical strategy uses five different steps to calculate the degree of multifractality in the

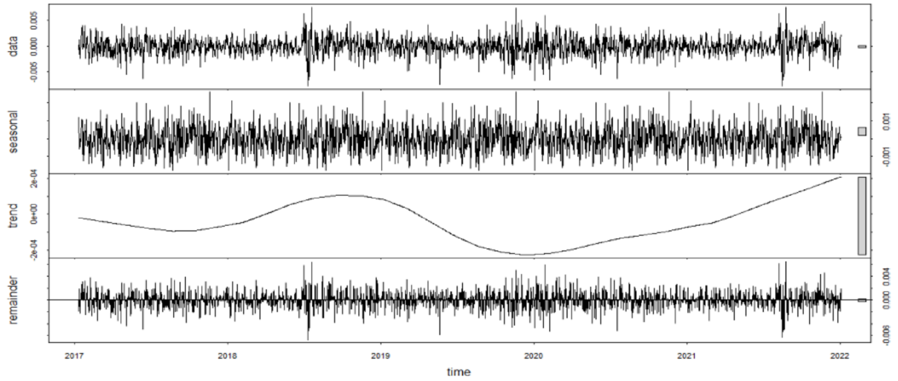

Fig. 6 Seasonal and Trend Decomposition using Loess (STL) of USD/EUR

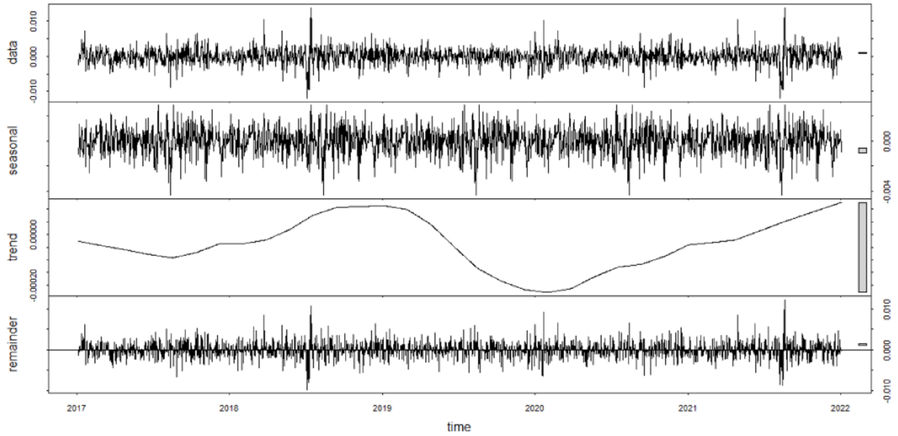

Fig. 7 Seasonal and Trend Decomposition using Loess (STL) of USD/GBP

spot rates series (Kantelhardt et al. 2002). In that vein, the MFDFA method can be expressed as follows: Let X_i be a non-stationary time series, with *N* indicating the length of the series and *i* ranging from 1 to *N*.

In Step 1, the profile/cumulative sum $Y_{(i)}$ is depicted as:

$$Y_{(i)} = \sum{}_{t=1}^{i} (x\left(k\right) - \bar{x}) \tag{3}$$

where $\bar{x}$ is the mean value of the whole series $\left(\bar{x} = \frac{1}{N} \sum{}_{i=1}^{N} x_i\right)$.

Step 2 approaches the dividing of profile/cumulative sum $Y_{(i)}$ into $N_s \equiv int\frac{N}{s}$ non-overlapping boxes of equal length *s*. The length of the whole series, representing with *N*, is reckoned for non-multiple for *s*. However, the analytical basis slightly overjumps part of profile $Y_{(i)}$ at the end of the sample. The empirics cover the full information when the similar technique repeats by initiating the process from the

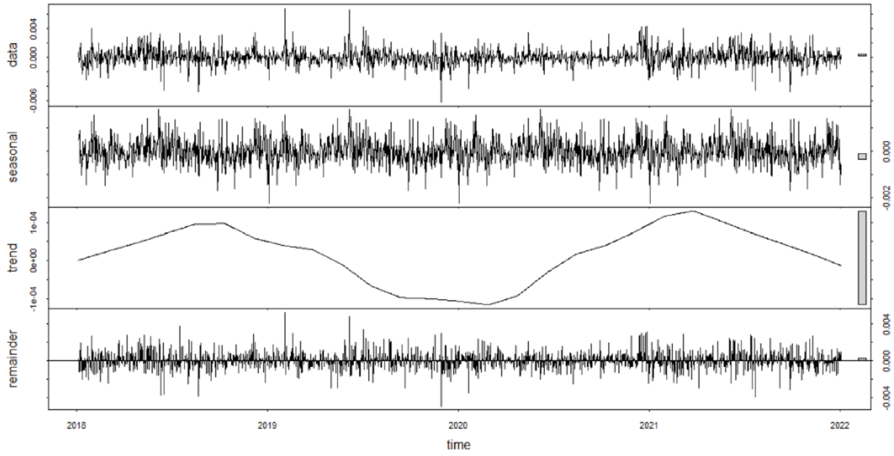

Fig. 8 Seasonal and Trend Decomposition using Loess (STL) of CNY/USD

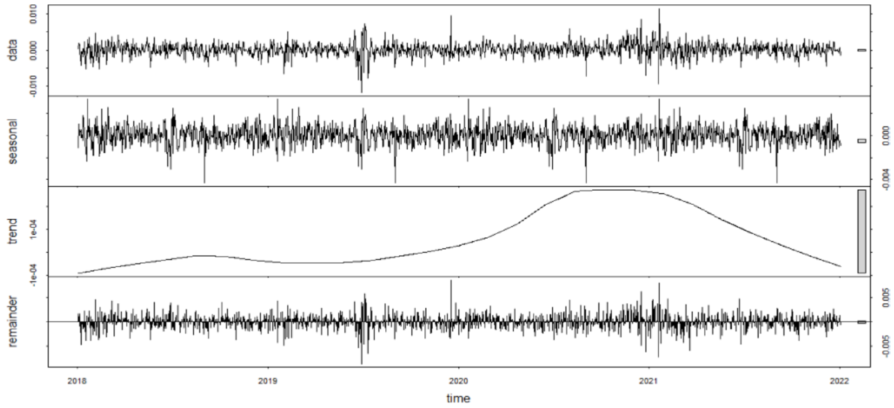

Fig. 9 Seasonal and Trend Decomposition using Loess (STL) of JPY/USD

opposite direction of given series Y_{ϑ}. Therefore, it agglomerates $2N_s$ segments altogether.

Moreover, Step 3 is used to measure the local trend of $2N_s$ by way of implementing least-square fitting polynomial $\widetilde{Y}_{\vartheta}$ for each segment of length ϑ. So that, the variance is calculated as follows (Kukacka and Kristoufek 2020):

$$F^2(s,\vartheta) = \frac{1}{s}\sum{}_{k=1}^{s}\{X[(\vartheta-1)s+k]-x_{\vartheta}(k)\}^2 \tag{4}$$

for each segment of length ϑ, and

$$F^2(s,\vartheta) = \frac{1}{s}\sum{}_{k=1}^{s}\{X[N-(\vartheta-N_s)s+k]-x_{\vartheta}(k)\}^2 \tag{5}$$

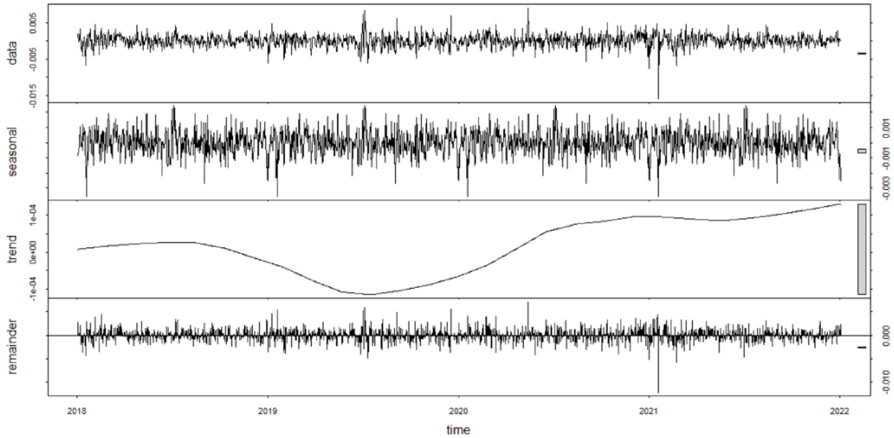

Fig. 10 Seasonal and Trend Decomposition using Loess (STL) of CHF/USD

for $\vartheta = N_{s+1,\ldots}, 2N_s$, where $x_\vartheta(k)$ is the polynomial fit in each segment of ϑ. The detrending process is repeated over a wide range of various sizes in window.

Besides, Step 4 measures the segments on average, which is initiated in Step 2, to assess the q-order fluctuation function F_q (Kukacka and Kristoufek 2020):

$$F_{q(s)} = \left\{ \frac{1}{2N_s} \sum {}_{\vartheta=1}^{2N_s} \left[F_s^2(\vartheta) \right]^{q/2} \right\}^{1/q} \tag{6}$$

where each estimated value of $q \neq 0$. On the other hand, the fluctuation function is estimated for $q = 0$ as follows:

$$F_{0(s)} = exp\left\{ \frac{1}{4N_s} \sum {}_{\vartheta=1}^{2N_s} ln\left[F_s^2(\vartheta) \right] \right\} \tag{7}$$

The q parameter leads us to differentiate each segment with small and large fluctuations. Therefore, the q parameter with positive and negative values is reliable to use for large and small fluctuations, respectively, where $F_{q(s)}$ is the increasing function of window size.

In the last step (i.e., Step 5) the scaling behavior of fluctuation functions is dealt within the estimation process, which is represented as the plots over the log-log plots of $F_{q(s)}$ for each value of q versus s (Ihlen 2012):

$$F_{q(s)} \sim s^{h(q)} \tag{8}$$

In consideration of Eq. (8), the series is assumed to be monofractal when there is a constancy in $h(q)$ and to be multifractal when there is an inconsistency in $h(q)$ for all q. How fast is $F_{q(s)}$ of local fluctuations increase depends on the pattern of s window. The presence of multifractal series leads to measure the estimators which are ranged between $h(q)$ and q. While the $h(q)$ is the scaling behavior of each segment with large fluctuations when q has positive values, the small fluctuations emerge in the estimation with negative values of q. There may evolve large numbers of iterations in estimations which refer that the multifractal series has smaller $h(q)$ together with the q values higher than zero. In the estimation process, the multifractal spectrum will be based on $=1$, $m=2$, and $m=3$. Accordingly, the q order is determined at $m=1$ to avoid overfitting (Lashermes et al. 2004; Mnif et al. 2020; Mnif and Jarboui 2021).

Regarding the MFDFA method, the generalized Hurst exponent (GHE) will be estimated where the Hurst exponent (Hurst 1951) is employed as a metric to illustrate whether the series is confronted with a financial explosion or bubbles. The primary importance of the GHE is initiated by the studies of Di Matteo et al. (2005) and Barunik and Kristoufek (2010) where the scaling behavior is estimated by the statistics in the following form, representing in Eq. (9):

$$K_q(\tau) = \sum{}_{t=0}^{N-\tau} |X(t+\tau) - X(t)|^q / \sum{}_{t=0}^{N-\tau} |X(t)|^q \tag{9}$$

According to Eq. (9), the series is assumed to be anti-persistent with no shape and lesser fractal quotient when $h(q) < 0.5$. If this is the case, the market is also assumed as being confronted with no herd behavior. On the other hand, the series may follow a random walk and thus be entirely stochastic in nature when $h(q) = 0.5$. Finally, the series is considered persistent with a clear shape, higher fractal quotient, and herd biased when $h(q) > 0.5$.

The early studies of Mandelbrot and van Ness (1968) and Mandelbrot (1972, 1974) measure the financial time series and the series of physical sciences using the local Hölder exponent (or roughness) in case of Fractal Brownian Motions (FBM). In essence, the FBM does not capture fat tails and the change in volatility. In this regard, they are supposed to be uncorrelated with the predictions of future returns or fluctuations in series. Rather, the FBM is used to model the tendency of price changes followed by the changes in the same (or opposite) direction. This study considers the multifractality in an extended form to measure the stochastic process in series where the moments are regarded as the basis of multifractality along with the scaling in moments of the process' increments (Mandelbrot et al. 1997). In that vein, the local Hölder (Hurst) exponent is estimated by taking limits as the side lengths of different regions tend to zero at (x, y):

$$d_{loc}(x, y) = lim_{n->\infty} Log\left(Prob(i_1, ..., i_n)\right) / Log\left(2^{-n}\right) \tag{10}$$

where *prob(* $i_1, ..., i_n$) represents the probability $pr(i_1) * .... * pr(i_n)$ if (x, y) is located in the square with address $i_1 ... i_n$. Therefore, the fractal dimension (*d*) is estimated as follows:

$$d = 2 - H \; when \; 0 < H < 1 \tag{11}$$

or

$$d = 1.5 - \alpha \ when\ 0 < \alpha < 1 \tag{12}$$

The scaling function of multifractality $\tau\ (q)$ may be attributed as concave or linear for multifractal and monofractal processes, respectively (Mnif and Jarboui 2021). The log-log plot of τ and $K_q\,(\tau\,)$ are measured for different levels of q. In particular, the statistics $K_q\,(\tau\,)$ with scaling power can be calculated for which the time series has a long-range power-law correlation:

$$K_q\,(\tau\,) \sim c\tau^{\,qh(q)} \tag{13}$$

The Renyi exponent $\tau\ (q)$ can be also used as an estimation of $h\,(q)$:

$$\tau\ (q) = qh\,(q) - 1 \tag{14}$$

The Renyi exponent $\tau\ (q)$ has two different forms where the multifractal spectrum is used as a benchmark to assess whether the series is monofractal or multifractal. On the one hand, the first form is based on the generalized Hurst exponent (GHE), calculating as follows:

$$h\,(q) = \frac{1 + \tau\ (q)}{q} \tag{15}$$

On the other hand, the second form employs the generalized fractal dimension (GFD):

$$d\,(q) = \frac{\tau\ (q)}{q\ - 1} \tag{16}$$

Besides, the Legendre transformation is used to obtain the GFD:

$$\alpha\ = h\,(q) +\ q\frac{dh_q}{d_q} - \tau\ _q \tag{17}$$

where α is the Hölder exponent.

In this regard, the singularity spectrum $f\,(\alpha\,)$ is measured as follows:

$$f\,(\alpha\,) = q\alpha\ \ - \tau\ _q \tag{18}$$

where $\tau\ _q$ is equal to $qh\,(q) - 1$.

The scaling range is located among the $s_{min} = 10$ and $s_{max} = T/4$ (Rizvi et al. 2014) for measuring the series through the implementation of MFDFA approach, where T represents the series' length of selected exchange rates. Accordingly, higher multifractality is shown by higher variability of $h\,(q)$. In this regard, the multifractality is calculated as $\Delta\ h = h_{(qmin)} - h_{(qmax)}$ with $h\,(q)$ decreases as q increases (Zunino et al. 2008). This also shows that the higher the value of $\Delta\ h$, the greater the series is multifractal. What is more, the higher width of multiple spectra refers that the selected exchange rates are less effective since the multifractality is negatively

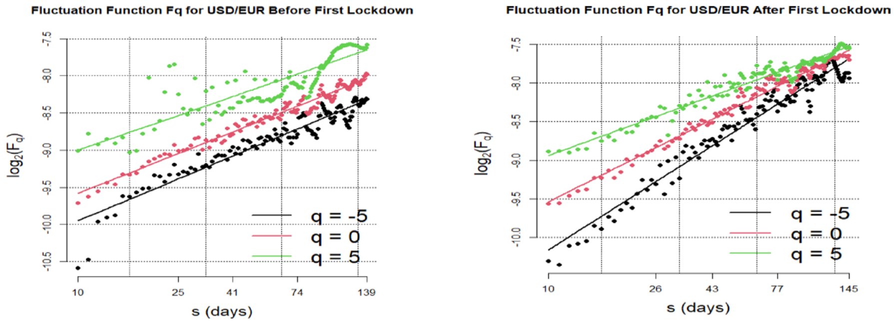

Fig. 11 The MFDFA results for 5-day week fluctuation of USD/EUR

correlated with market efficiency (Domino 2011; Caraiani 2012; Aslam et al. 2020b). All these different steps in the empirical procedure are done with the Rstudio package "MFDFA" developed by Laib et al. (2018a, b).

In consideration of the MFDFA approach, the Magnitude of Long-Memory (MLM) which is based on the generalized Hurst exponent (GHE) is calculated to determine the change in market efficiency (Mnif et al. 2020). The MLM (inefficiency) index refers to the case that fluctuations, which are ranged between the smaller $h(-5)$ and the larger $h(5)$ orders, follow the random walk process. In other words, the fluctuations in exchange rates are considered efficient with no long memory and herd investing when MLM is equal to zero. In that sense, the higher (lower) value of MLM implies a higher (lower) level of long memory and a higher (lower) level of herd investing in exchange rates. The market efficiency level and the degree of herd investing are calculated by the MLM (inefficiency) index using the following form of estimation (Khuntia and Pattanayak 2020):

$$MLM = \frac{1}{2}\left(|h(-5) - 0.5| + |h(5) - 0.5|\right) \tag{19}$$

Empirical findings

The primary concern in empirical process is to analyze the multifractal series with non-normal distribution to assess whether it is led by various traces. Figures (11, 12, 13, 14, 15) represent the standard MFDFA results for the remaining inputs of selected exchange rates (i.e., USD/EUR, USD/GBP, CNY/USD, JPY/USD, and CHF/USD). Each figure refers that the log-log relationship between $F(q)$ and s is described as a clear shape and in a straight line. Besides, the Hurst exponent is measured by $F_2(s,\vartheta)$ where the stationary of given series tends to be calculated for different traces of Hurst exponent in such case that $q=2$ for the scaling exponent. Furthermore, each figure shows the values of GHE where the trends of estimated values have negative slopes thereby implying the multifractality in time variations of the remaining component.

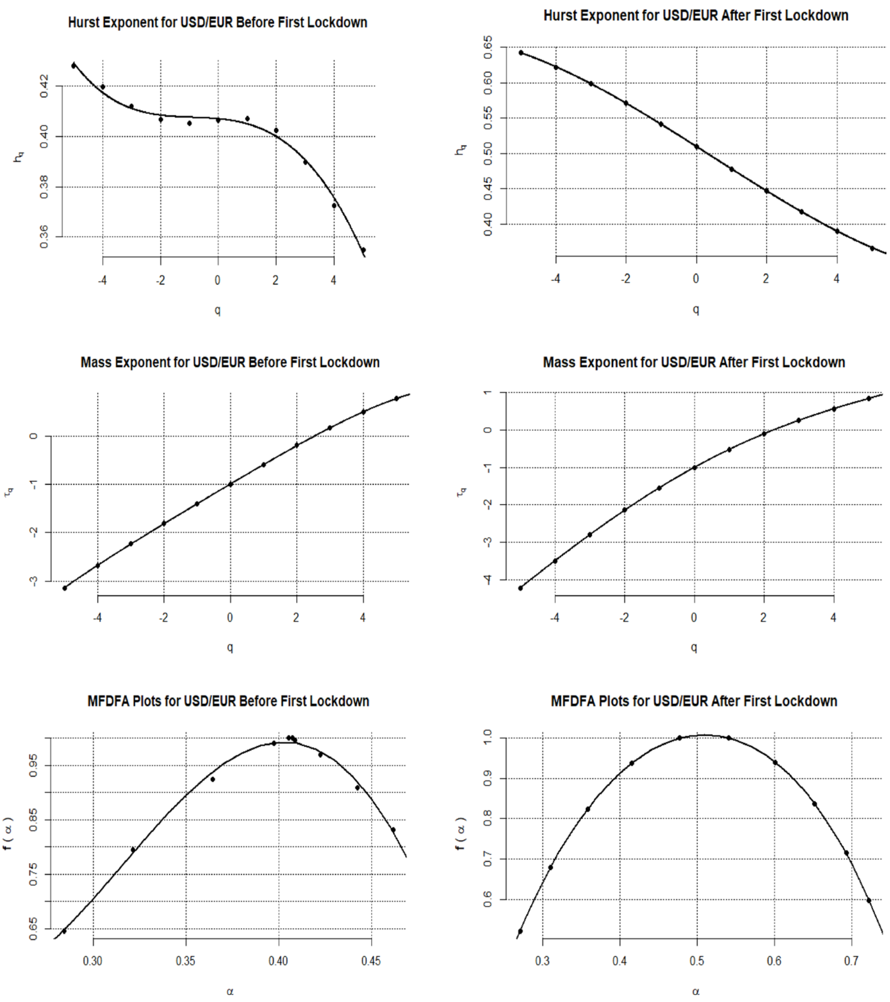

Fig. 11 (continued)

Regarding further estimations of multifractal dimension, the Renyi exponent $\tau\ (q)$ and the singularity spectrum f_{α} are estimated through Eqs. (14)-(18). The overall results refer to the case that the monofractal series is linear, whereas the multifractal series have a non-linear trend. The exponential shape of the Renyi exponent implies that the series is subjected to a multifractal spectrum. What is more, a single-humped shape of the multifractal spectrum indicates that the whole series are multifractal.

In the final step of the empirical process, the range of Δh will be measured to analyze the presence of a multifractal spectrum and to identify the degree of multifractality in series. In this sense, the larger (smaller) the range, the higher (lower) the multifractality (Kantelhardt et al. 2002).

Table 2 shows the empirical results for the generalized Hurst exponent over the range of $q \in$ [-5, 5] for given foreign exchange rates. In particular, the values of $h\ (q)$

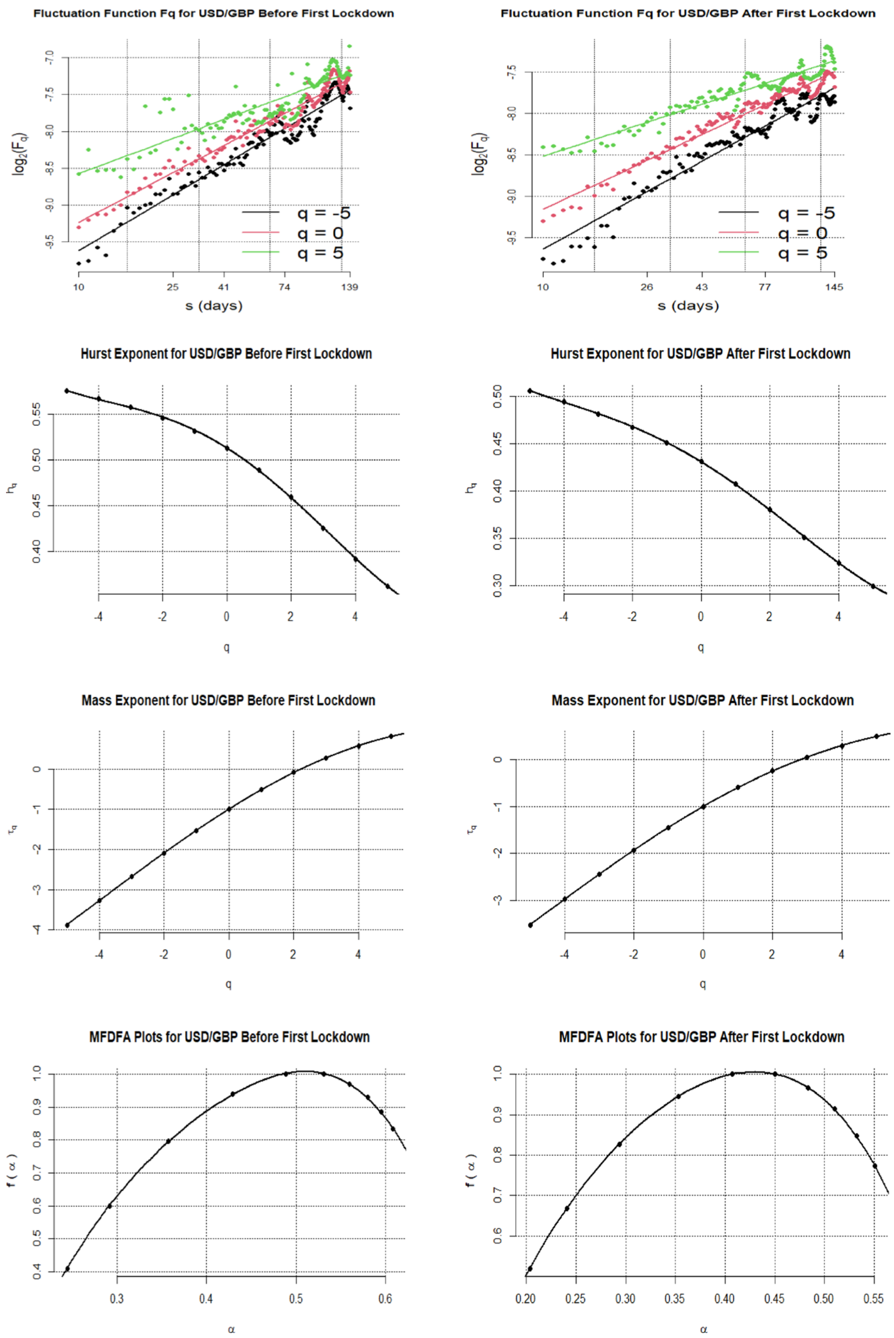

Fig. 12 The MFDFA results for 5-day week fluctuation of USD/GBP

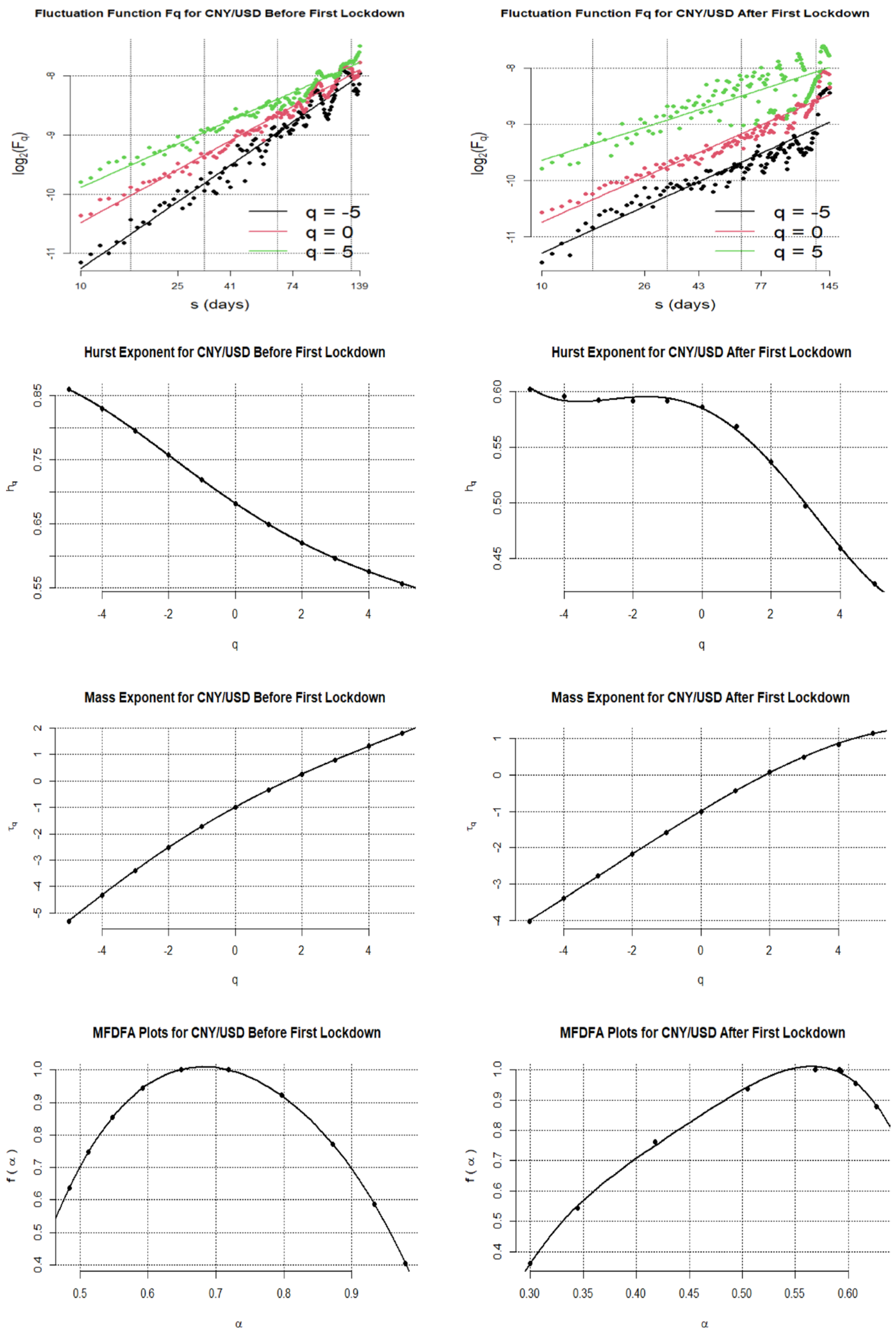

Fig. 13 The MFDFA results for 5-day week fluctuation of CNY/USD

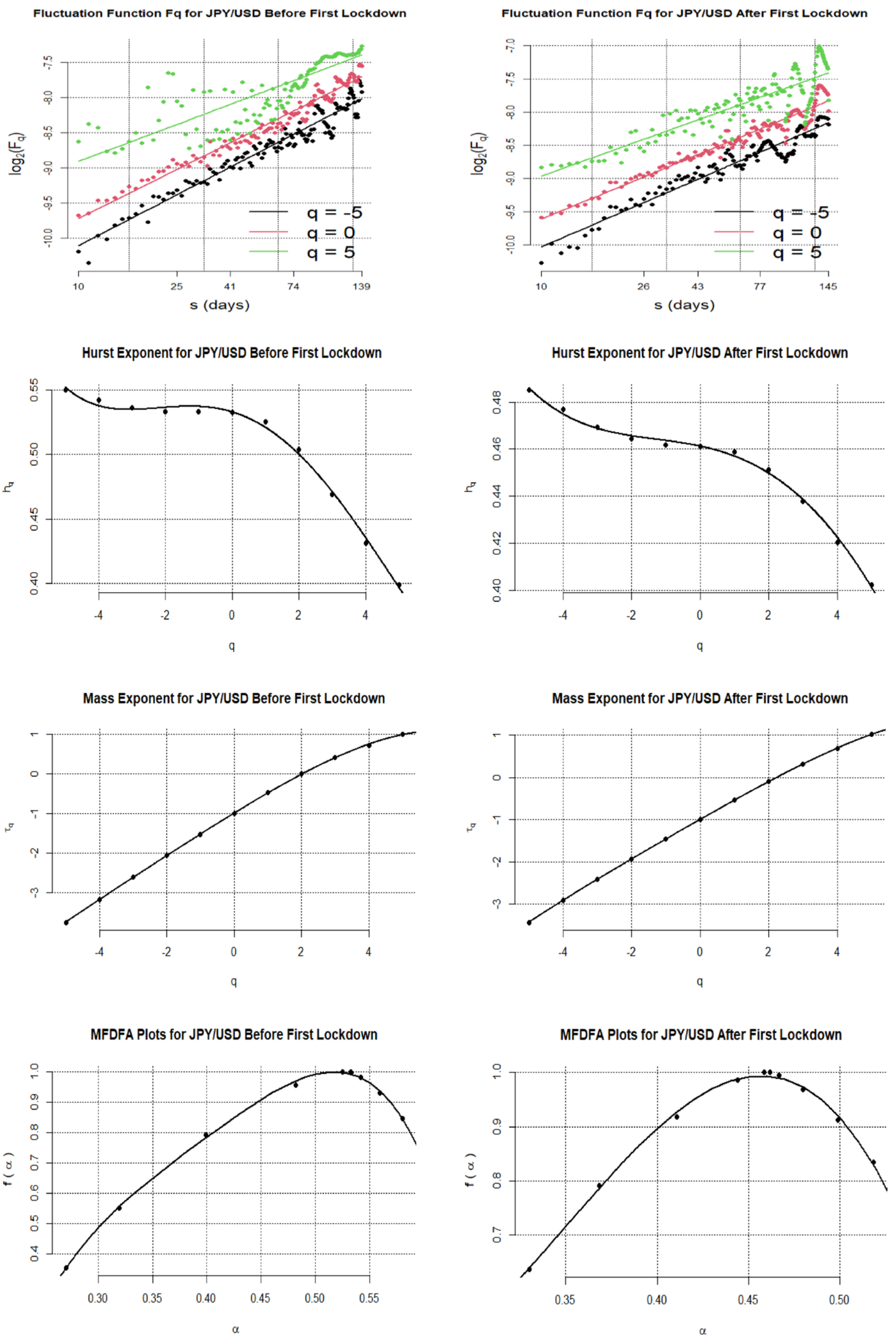

Fig. 14 The MFDFA results for 5-day week fluctuation of JPY/USD

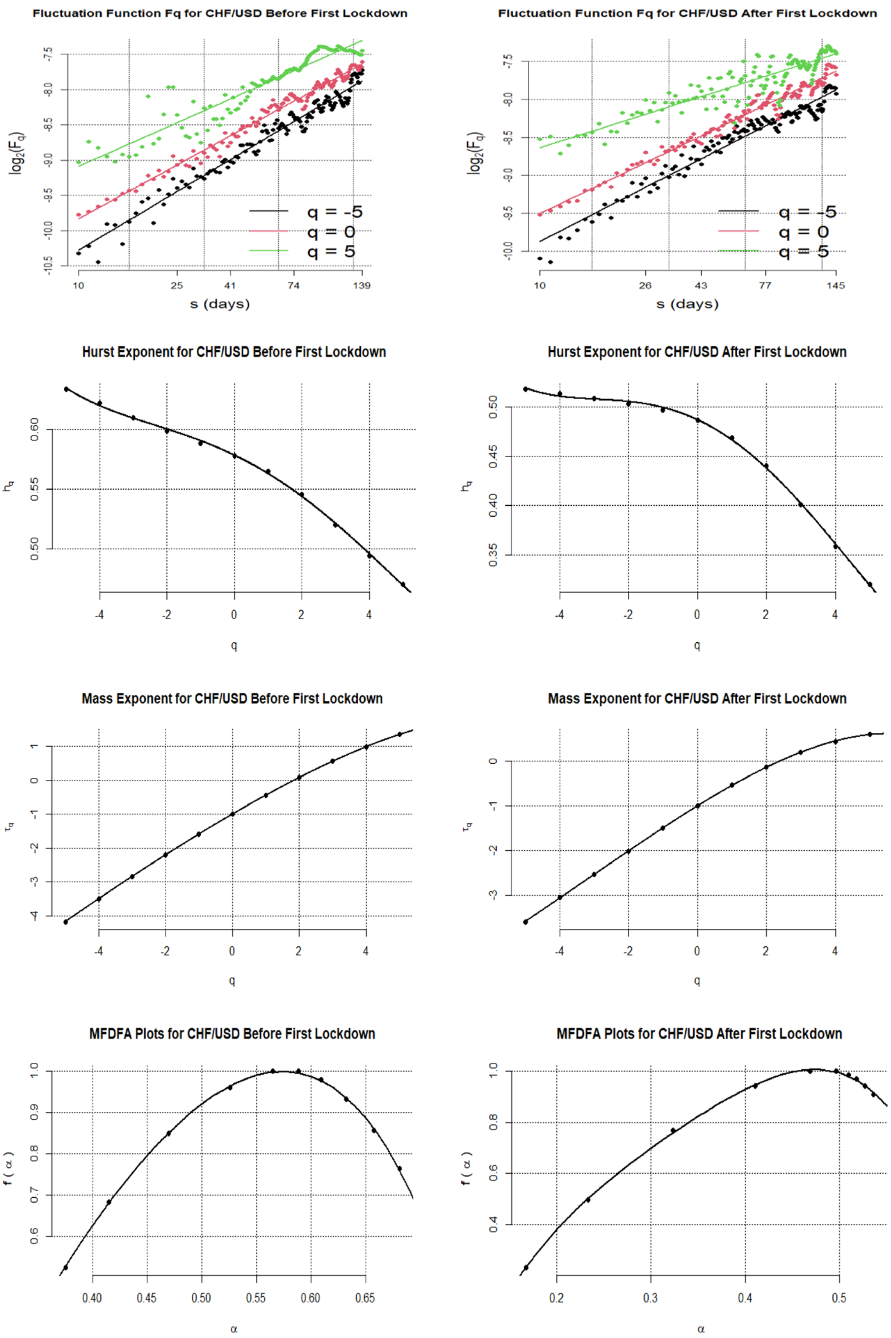

Fig. 15 The MFDFA results for 5-day week fluctuation of CHF/USD

Table 2 Generalized Hurst exponent for $-5<q<5$

q	USD/EUR		USD/GBP		CNY/USD		JPY/USD		CHF/USD	
	Before	After	Before	After	Before	After	Before	After	Before	After
-5	0.4281	0.6419	0.5750	0.5053	0.8597	0.6021	0.5497	0.4851	0.6336	0.5177
-4	0.4197	0.6218	0.5667	0.4940	0.8300	0.5960	0.5420	0.4768	0.6218	0.5131
-3	0.4121	0.5980	0.5571	0.4813	0.7955	0.5923	0.5362	0.4695	0.6099	0.5084
-2	0.4069	0.5709	0.5456	0.4669	0.7575	0.5916	0.5332	0.4643	0.5987	0.5034
-1	0.4052	0.5410	0.5312	0.4503	0.7186	0.5917	0.5329	0.4618	0.5885	0.4969
0	0.4064	0.5096	0.5128	0.4306	0.6817	0.5863	0.5324	0.4610	0.5781	0.4866
1	0.4072	0.4778	0.4889	0.4069	0.6489	0.5687	0.5252	0.4587	0.5647	0.4688
2	0.4023	0.4467	0.4590	0.3798	0.6205	0.5368	0.5037	0.4514	0.5452	0.4399
3	0.3896	0.4173	0.4251	0.3510	0.5962	0.4971	0.4689	0.4378	0.5201	0.4011
4	0.3725	0.3905	0.3917	0.3234	0.5752	0.4590	0.4315	0.4204	0.4938	0.3591
5	0.3548	0.3666	0.3623	0.2994	0.5570	0.4271	0.3992	0.4023	0.4701	0.3207
Δh	*0.0733*	*0.2753*	*0.2127*	*0.2059*	*0.3027*	*0.1750*	*0.1505*	*0.0828*	*0.1635*	*0.1970*

in each spot rate have a declining trend and thus it implies that the series are confronted with multifractality in time fluctuation of the remaining components (Laib et al. 2018a, b). On the one hand, the widest range of generalized Hurst exponent $\Delta h(q)$ before the first lockdown is tracked by CNY/USD followed by USD/GBP (0.3027 and 0.2127, respectively), referring to the highest levels of multifractality (i.e., the least efficient spot rates before the first lockdown). Besides, the narrowest range of generalized Hurst exponent $\Delta h(q)$ is held by USD/EUR and JPY/USD (0.0733 and 0.1505, respectively), implying that these spot rates have the lowest multifractality levels (i.e., greatest market efficiency) before the first lockdown. On the other hand, the widest range of generalized Hurst exponent $\Delta h(q)$ after the first lockdown (i.e., post-lockdown period) is in USD/EUR followed by USD/GBP (0.2753 and 0.2059, respectively), referring to the highest levels of multifractality (i.e., the least efficient spot rates after the first lockdown). However, the narrowest range of generalized Hurst exponent $\Delta h(q)$ is in JPY/USD and CNY/USD (0.0828 and 0.1750, respectively), indicating that these spot rates have the lowest levels of multifractality (greatest market efficiency) for the post-lockdown period.

Moreover, Table 3 summarizes the multifractal spectrum (α) from upper and lower probabilities before and after the first lockdown period. The estimated values of $\Delta h(q)$ show that selected spot rates have high fractality and have become less efficient after the first lockdown across the financial markets. Regarding the generalized Hurst exponent $\Delta h(q)$, the degree of q is close to 0.5 which indicates that the selected foreign exchange rates show persistent behavior, meaning that any change (positive/negative) in pre-first-lockdown period would be followed by the same (positive/negative) attitude for the post-first-lockdown period. What is more, the estimated values refer to that they are predictable thereby indicating evidence towards market inefficiency for selected foreign exchange rates after the first lockdown. Therefore, the trend strategies could lead to a burst of abnormal returns from those spot rates during the given time range (Caporale et al. 2018).

The multifractality results are summarized in Table 4 and the multifractal patterns are depicted in Table 5. While the estimated values of generalized Hurst exponent $\Delta h(q)$ show that the selected foreign exchange rates exhibit persistent behavior and

Table 3 Multifractal spectrum (α) from upper to lower probabilities

α	USD/EUR		USD/GBP		CNY/USD		JPY/USD		CHF/USD	
	Before	After	Before	After	Before	After	Before	After	Before	After
1	0.4617	0.7223	0.6082	0.5505	0.9785	0.6265	0.5805	0.5183	0.6808	0.5361
2	0.4425	0.6932	0.5955	0.5321	0.9335	0.6071	0.5594	0.4987	0.6575	0.5272
3	0.4225	0.6522	0.5801	0.5101	0.8715	0.5937	0.5422	0.4799	0.6323	0.5184
4	0.4086	0.6008	0.5600	0.4835	0.7964	0.5915	0.5335	0.4668	0.6089	0.5099
5	0.4052	0.5410	0.5312	0.4503	0.7186	0.5917	0.5329	0.4618	0.5885	0.4969
6	0.4072	0.4778	0.4889	0.4069	0.6489	0.5687	0.5252	0.4587	0.5647	0.4688
7	0.3974	0.4156	0.4291	0.3527	0.5921	0.5049	0.4822	0.4441	0.5257	0.4110
8	0.3642	0.3585	0.3573	0.2934	0.5476	0.4177	0.3993	0.4106	0.4699	0.3235
9	0.3212	0.3101	0.2915	0.2406	0.5122	0.3447	0.3193	0.3682	0.4149	0.2331
10	0.2840	0.2710	0.2442	0.2034	0.4842	0.2995	0.2700	0.3299	0.3753	0.1671
$\Delta\alpha$	*0.1777*	*0.4513*	*0.3640*	*0.3471*	*0.4943*	*0.3270*	*0.3105*	*0.1884*	*0.3055*	*0.3690*

Table 4 Multifractality results

Exchange Rates		Δh	Δα	Hurst Average	Multifractal Spectrum Average (α)	Fractal Dimension (d)	MLM (Inefficiency) Index
USD/EUR	Before	0.0733	0.1777	0.4004	0.3915	1.9267	0.1086
	After	0.2753	0.4513	0.5074	0.5042	1.7247	0.1376
USD/GBP	Before	0.2127	0.3640	0.4923	0.4686	1.7873	0.1063
	After	0.2059	0.3471	0.4171	0.4023	1.2059	0.1029
CNY/USD	Before	0.3027	0.4943	0.6946	0.7084	1.6973	0.2084
	After	0.1750	0.3270	0.5499	0.5146	1.8250	0.0875
JPY/USD	Before	0.1505	0.3105	0.5049	0.4745	1.8495	0.0753
	After	0.0828	0.1884	0.4535	0.4437	1.9172	0.0563
CHF/USD	Before	0.1635	0.3055	0.5659	0.5519	1.8365	0.0817
	After	0.1970	0.3690	0.4560	0.4192	1.8030	0.0985

Table 5 Summary results for forex market

Exchange Rates	Herd investing	Market inefficiency
USD/EUR	↑	↑
USD/GBP	↑	↓
CNY/USD	↓	↓
JPY/USD	↓	↓
CHF/USD	↑	↑

thus they show predictable background with evidence of market inefficiency for the given time horizon where the herding biases and market inefficiency patterns are much different from each other across the spot rates. In essence, the width of multifractal spectrum Δα indicates that increases in weighted average coincided with the increases in multifractality (Lu et al. 2013). In consideration of abnormal changes in the average of multifractal spectrum among two different periods, the estimated values of those changes refer to the case that the multifractality increased for USD/EUR and CHF/USD. To get more robust and consistent results for those findings, the MLM (inefficiency) index is measured based on $h\,(q)$ in Table 4 where the higher values of MLM indicate that market inefficiency increases for relevant foreign exchange rates. In this regard, from pre-first-lockdown to post-first-lockdown period, USD/EUR and CHF/USD exchange rates became more multifractal and less efficient.

Furthermore, the presence of herd biases in spot rates is documented in Table 4. Some part of the relevant literature suggests that the fractal theory (which depends on the theoretical trace of Hausdorff topology) may have an opportunity to use for assessing the degree of herding behavior in financial markets. Following this fractal theory, the fractal dimension (*d*) is calculated to analyze the change in herding biases across the selected foreign exchange rates and different time dimensions. The estimated values of fractal dimension (*d*) indicate that herding behavior is statistically relevant for some degrees among the selected spot rates and particularly increased for USD/EUR, USD/GBP, and CHF/USD from pre- to post-first-lockdown period. Besides, the ranking values of fractal dimension (*d*) provide a way to reveal the weight of herding biases in which those spot rates exhibited an increase in the degree of herding behavior during the post-first-lockdown period. Regarding the ranking of estimated values of fractal dimension (*d*), the CNY/USD exchange rate has the highest degree of herding behavior (1.6973) before the first lockdown period and the USD/GBP exchange rate has the highest degree of herding behavior (1.2059) after the first lockdown period.

Finally, the estimated values of the MLM (inefficiency) index show that the selected foreign exchange rates are inefficient to various degrees among the two periods. The highest level of MLM (inefficiency) index is attributed to CNY/USD exchange rate (0.2084) before the first lockdown period and the USD/EUR exchange rate (0.1376) after the first lockdown period. Besides, the MLM (inefficiency) index increased for USD/EUR and CHF/USD exchange rates among the given two periods, referring to the spread of those spot rates across the financial relations thus the expansion of transactions of those currencies among the firms, institutions and individual investors who have bought those currencies in transactions have negative effects on the degree of market inefficiency.

Concluding remarks

This study examines the degree of market efficiency and herding behavior across five major foreign exchange rates - USD/EUR, USD/GBP, CNY/USD, JPY/USD, and CHF/USD. To this end, the generalized Hurst exponent (GHE) and the magnitude of long-memory (MLM) methods were applied to evaluate the level of fractality using the multifractal detrended fluctuation analysis (MFDFA) for both the pre-first-lockdown and post-first-lockdown periods. Prior to the MFDFA, the Seasonal and Trend Decomposition using Loess (STL) approach was employed to detect the presence of multifractality in the fluctuations of the exchange rate series. Thus, the core objective of the study was to determine whether these spot rates became more susceptible to herd-driven investment behavior before and after the first COVID-19 lockdown.

Overall, the GHE estimates demonstrated that the selected exchange rates exhibited multifractal characteristics to varying degrees throughout the sample period.

Nevertheless, the intensity of herding and market inefficiency differed noticeably between the two subperiods. Specifically, changes in the average values of the multifractal spectrum showed that multifractality increased for the USD/EUR rate from the pre-lockdown to the post-lockdown period. In other words, the lockdown appeared to amplify herding tendencies and market inefficiency in USD/EUR transactions. Additionally, the MLM-based inefficiency index indicated that the USD/EUR and CHF/USD rates became more multifractal and less efficient following the first lockdown.

The fractal dimension (d), calculated for each spot rate to assess variations in herding behavior during the pandemic, further supported these findings. The results indicated that herding behavior was statistically significant to varying extents and increased particularly for USD/EUR, USD/GBP, and CHF/USD in the post-lockdown period. Ranking the fractal dimension values revealed that CNY/USD exhibited the highest degree of herding (1.6973) before the lockdown, whereas USD/GBP displayed the strongest herding tendency (1.2059) in the post-lockdown stage.

Furthermore, the MLM (inefficiency) index showed that all selected spot rates were inefficient to different degrees. The highest inefficiency was observed in the CNY/USD rate (0.2084) before the first lockdown and in the USD/EUR rate (0.1376) afterwards. Moreover, the increase in the inefficiency index for USD/EUR and CHF/USD across the two periods suggests that these rates experienced broader market-wide effects in terms of transaction volumes.

In light of these empirical results, the study offers valuable insights for investors regarding shifts in herding behavior and market inefficiency in the post-pandemic era. These findings may facilitate a better understanding of market performance during mildly turbulent periods such as those experienced during COVID-19. Future research is encouraged to explore additional dimensions of herding dynamics and market inefficiency across the foreign exchange market by incorporating a wider range of financial instruments and services.

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Declarations

Competing interests The authors declare no competing interests.

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References

Abounoori E, Shahrazi M, Rasekhi S (2012) An investigation of forex market efficiency based on detrended fluctuation analysis: a case study for Iran. Physica A 391(11):3170–3179. https://doi.org/10.1016/j.physa.2011.12.045

Adams RB (2021) Trust in finance: values matter. J Jpn Int Econ 60:101123. https://doi.org/10.1016/j.jjie.2021.101123

Adrangi B, Chatrath A, Dhanda KK, Raffiee K (2001) Chaos in oil prices? Evidence from futures markets. Energy Econ 23(4):405–425. https://doi.org/10.1016/S0140-9883(00)00079-7

Akhtaruzzaman M, Boubaker S, Sensoy A (2021) Financial contagion during COVID–19 crisis. Financ Res Lett 38:101604. https://doi.org/10.1016/j.frl.2020.101604

Alber N (2020) The effect of coronavirus spread on stock markets: The case of the worst 6 countries. SSRN Electronic Journal, Available at: https://ssrn.com/abstract=3578080

Albulescu CT (2021) COVID-19 and the United States financial markets' volatility. Financ Res Lett 38:101699. https://doi.org/10.1016/j.frl.2020.101699

Ambros M, Frenkel M, Huynh TLD, Kilinc M (2021) COVID-19 pandemic news and stock market reaction during the onset of the crisis: evidence from high-frequency data. Appl Econ Lett 28(19):1686–1689. https://doi.org/10.1080/13504851.2020.1851643

Arshad S, Rizvi SAR, Haroon O (2019) Understanding Asian emerging stock markets. Bull Mon Econ Bank 21:495–510. https://doi.org/10.21098/bemp.v0i0.983

Ashraf BN (2020) Stock market's reaction to COVID-19: cases or fatalities? Res Int Bus Finance 54:101249. https://doi.org/10.1016/j.ribaf.2020.101249

Ashraf BN (2021) Stock markets' reaction to Covid-19: moderating role of national culture. Financ Res Lett 41:101857. https://doi.org/10.1016/j.frl.2020.101857

Aslam F, Aziz S, Nguyen DK, Mughal KS, Khan M (2020aa) On the efficiency of foreign exchange markets in times of the COVID-19 pandemic. Technol Forecast Soc Change 161:120261. https://doi.org/10.1016/j.techfore.2020a.120261

Aslam F, Mohti W, Ferreira P (2020b) Evidence of intraday multifractality in European stock markets during the recent coronavirus (COVID-19) outbreak. Int J Financ Stud 8(2):31. https://doi.org/10.3390/ijfs8020031

Aslam F, Ferreira P, Ali H, Kauser S (2022) Herding behavior during the COVID-19 pandemic: a comparison between Asian and European stock markets based on intraday multifractality. Eurasian Econ Rev 12(2):333–359. https://doi.org/10.1007/s40822-021-00191-4

Ayittey FK, Ayittey MK, Chiwero NB, Kamasah JS, Dzuvor C (2020) Economic impacts of Wuhan 2019-nCoV on China and the world. J Med Virol 92(5):473–475. https://doi.org/10.1002/jmv.25706

Bachelier L (1900) Theory of speculation in the random character of stock market prices. MIT Press, Cambridge

Baker S, Bloom N, Davis SJ, Kost K, Sammon M, Viratyosin T (2020) The unprecedented stock market reaction to COVID-19. Rev Asset Pricing Stud 10(4):742–758. https://doi.org/10.1093/rapstu/raaa008

Banerjee AV (1992) A simple model of herd behavior. Q J Econ 107(3):797–817. https://doi.org/10.2307/2118364

Barunik J, Kristoufek L (2010) On Hurst exponent estimation under heavy-tailed distributions. Physica A Stat Mech Appl 389(18):3844–3855. https://doi.org/10.1016/j.physa.2010.05.025

Basuony MAK, Bouaddi M, Ali H, EmadEldeen R (2021) The effect of COVID-19 pandemic on global stock markets: Return, volatility, and bad state probability dynamics. J Public Affairs e2761. https://doi.org/10.1002/pa.2761

Bernstein PL (1999) A new look at the efficient market hypothesis. J Portfolio Manag 25(2):1–2

Bettendorf T, Chen W (2013) Are there bubbles in the sterling-dollar exchange rate? New evidence from sequential ADF tests. Econ Lett 120(2):350–353. https://doi.org/10.1016/j.econlet.2013.04.039

Caporale GM, Gil-Alana L, Plastun A (2018) Persistence in the cryptocurrency market. Res Int Bus Finance 46:141–148. https://doi.org/10.1016/j.ribaf.2018.01.002

Caraiani P (2012) Evidence of multifractality from emerging European stock markets. PLoS One 7(7):40693. https://doi.org/10.1371/journal.pone.0040693

Cepoi C-O (2020) Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil. Finance Res Lett 36:101658. https://doi.org/10.1016/j.frl.2020.101658

Chiang TC, Zheng D (2010) An empirical analysis of herd behavior in global stock markets. J Bank Finance 34(8):1911–1921. https://doi.org/10.1016/j.jbankfin.2009.12.014
Chiang SM, Lee YH, Su HM, Tzou YP (2010) Efficiency tests of foreign exchange markets for four Asian countries. Res Int Bus Finance 24(3):284–294. https://doi.org/10.1016/j.ribaf.2010.01.001
Choi SY (2020) Industry volatility and economic uncertainty due to the COVID-19 pandemic: evidence from wavelet coherence analysis. Financ Res Lett 37:101783. https://doi.org/10.1016/j.frl.2020.101783
Claessens S, Dasgupta S, Glen J (1995) Return behavior in emerging stock markets. World Bank Econ Rev 9(1):131–151
Cleveland R, Cleveland W, McRae J, Terpenning I (1990) STL: a seasonal-trend decomposition procedure based on loess. J Off Stat 6(1):3–73
Conlon T, McGee R (2020) Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. Financ Res Lett 35:101607. https://doi.org/10.1016/j.frl.2020.101607
Cont R (2007) Volatility clustering in financial markets: empirical facts and agent-based models. In: Teyssière G, Kirman AP (eds) Long Memory in Economics. Springer, Berlin, pp 289–309
Contessi S, de Pace P (2021) The international spread of COVID-19 stock market collapses. Financ Res Lett 42:101894. https://doi.org/10.1016/j.frl.2020.101894
Cujean J, Hasler M (2017) Why does return predictability concentrate in bad times? J Finance 72(6):2717–2758. https://doi.org/10.1111/jofi.12544
Da Gama Silva PVJ, Klotzle MC, Pinto ACF, Gomes LL (2019) Herding behavior and contagion in the cryptocurrency market. J Behav Exp Finance 22:41–50. https://doi.org/10.1016/j.jbef.2019.01.006
Dhall R, Singh B (2020) The COVID-19 pandemic and herding behaviour: evidence from India's stock market. Millenn Asia 11(3):366–390. https://doi.org/10.1177/0976399620964635
Di Matteo T, Aste T, Dacorogna MM (2005) Long-term memories of developed and emerging markets: using the scaling analysis to characterize their stage of development. J Bank Finance 29(4):827–851. https://doi.org/10.1016/j.jbankfin.2004.08.004
Domino K (2011) The use of the Hurst exponent to predict changes in trends on the Warsaw stock exchange. Phys A 390(1):98–109. https://doi.org/10.1016/j.physa.2010.04.015
Dornbusch R (1976) Expectations and exchange rate dynamics. J Polit Econ 84(6):1161–1176
Dotsika F, Watkins A (2017) Identifying potentially disruptive trends by means of keyword network analysis. Technol Forecast Soc Change 119:114–127. https://doi.org/10.1016/j.techfore.2017.03.020
Dowla A (1995) Efficiency of the black market for foreign exchange. Int Econ J 9(2):89–100. https://doi.org/10.1080/10168739500000014
Dzielinski M (2011) News sensitivity and the cross-section of stock returns. NCRR Finrisk Working Paper 719. https://doi.org/10.2139/SSRN.1889030
Engelhardt N, Krause M, Neukirchen D, Posch P (2020) What drives stock during the corona-crash? News attention vs. rational expectation. Sustainability 12(12):5014. https://doi.org/10.3390/su12125014
Engelhardt N, Krause M, Neukirchen D, Posch P (2021) Trust and stock market volatility during the COVID-19 crisis. Fin Res Lett 38:101873. https://doi.org/10.1016/j.frl.2020.101873
Fama FE (1965) Random walks in stock market prices. Financ Anal J 21(5):55–59
Fama FE (1991) Efficient capital markets: II. J Finance 46(5):1575–1617. https://doi.org/10.2307/2328565
Fang H, Chung C-P, Lee Y-H, Yang X (2021) The effect of COVID-19 on herding behavior in Eastern European stock markets. Front Public Health 9:1–9. https://doi.org/10.3389/fpubh.2021.695931
Filip A, Pochea M, Pece A (2015) The herding behaviour of investors in the CEE stock markets. Procedia Econ Finance 32:307–315. https://doi.org/10.1016/S2212-5671(15)01397-0
Goodell JW (2020) COVID-19 and finance: agendas for future research. Financ Res Lett 35:101512. https://doi.org/10.1016/j.frl.2020.101512
Gopikrishnan P, Plerou V, Gabaix X, Amaral LAN, Stanley HE (2001) Price fluctuations and market activity. Physica A 299(1–2):137–143. https://doi.org/10.1016/S0378-4371(01)00288-6
Grossman SJ, Stiglitz JE (1980) On the impossibility of informationally efficient markets. Am Econ Rev 70(3):393–408
Han C, Wang Y, Ning Y (2019) Comparative analysis of the multifractality and efficiency of exchange markets: evidence from exchange rates dynamics of major world currencies. Physica A: Statistical Mechanics and its Applications 535:122365. https://doi.org/10.1016/j.physa.2019.122365
Haroon O, Rizvi SAR (2020) Flatten the curve and stock market liquidity – an inquiry into emerging economies. Emerg Mark Finance Trade 56(10):2151–2161. https://doi.org/10.1080/1540496X.2020.1784716

Hong H, Bian Z, Lee CC (2021) COVID-19 and instability of stock market performance: Evidence from the U.S. Financ Innov 7:12. https://doi.org/10.1186/s40854-021-00229-1
Hu Y, Oxley L (2017) Are there bubbles in exchange rates? Some new evidence from G10 and emerging market economies. Econ Model 64:419–442. https://doi.org/10.1016/j.econmod.2017.02.022
Hurst HE (1951) Long-term storage capacity of reservoirs. Trans Am Soc Civ Eng 116(1):770–799. https://doi.org/10.1061/TACEAT.0006518
Ihlen EAF (2012) Introduction to multifractal detrended fluctuation analysis in matlab. Front Physiol 3:141. https://doi.org/10.3389/fphys.2012.00141
Iwatsubo K, Kitamura Y (2009) Intraday evidence of the informational efficiency of the yen/dollar exchange rate. Appl Financ Econ 19(14):1103–1115. https://doi.org/10.1080/09603100802389015
Iyke BN (2019) A test of the efficiency of the foreign exchange market in Indonesia. Bull Mon Econ Bank 21(12):439–464. https://doi.org/10.21098/bemp.v0i0.976
Iyke BN (2020) COVID-19: the reaction of US oil and gas producers to the pandemic. Energy Res Lett 1(2). https://doi.org/10.46557/001c.13912
Jacobsen B, Dannenburg D (2003) Volatility clustering in monthly stock returns. J Empir Finance 10(4):479–503. https://doi.org/10.1016/S0927-5398(02)00071-3
Kantelhardt JW, Zschiegner SA, Koscielny-Bunde E, Havlin S, Bunde A, Stanley HE (2002) Multifractal detrended fluctuation analysis of nonstationary time series. Phys A 316(1–4):87–114. https://doi.org/10.1016/S0378-4371(02)01383-3
Khuntia S, Pattanayak JK (2020) Adaptive long memory in volatility of intra-day Bitcoin returns and the impact of trading volume. Financ Res Lett 32:101077. https://doi.org/10.1016/j.frl.2018.12.025
Kristoufek L (2011) Multifractal height cross-correlation analysis: a new method for analyzing long-range cross-correlations. EPL (Europhysics Letters) 95(6):68001. https://doi.org/10.1209/0295-5075/95/68001
Kühl M (2007) Cointegration in the foreign exchange market and market efficiency since the introduction of the euro: Evidence based on bivariate cointegration analyses. *Göttingen Discussion Papers*, 68
Kukacka J, Kristoufek L (2020) Do 'complex' financial models really lead to complex dynamics? Agent-based models and multifractality. J Econ Dyn Control 113:103855. https://doi.org/10.1016/j.jedc.2020.103855
Laib M, Golay J, Telesca L, Kanevski M (2018) Multifractal analysis of the time series of daily means of wind speed in complex regions. Chaos Solitons Fractals 109:118–127. https://doi.org/10.1016/j.chaos.2018a.02.024
Laib M, Telesca L, Kanevski M (2018) Long-range fluctuations and multifractality in connectivity density time series of a wind speed monitoring network. Chaos Interdiscip J Nonlinear Sci 28(3):033108. https://doi.org/10.1063/1.5022737
Lashermes B, Abry P, Chainais P (2004) New insights into the estimation of scaling exponents. Int J Wavelets Multiresolut Inf Process 2(4):497–523. https://doi.org/10.1142/S0219691304000597
Lazăr D, Todea A, Filip D (2012) Martingale difference hypothesis and financial crisis: empirical evidence from European emerging foreign exchange markets. Econ Syst 36(3):338–350. https://doi.org/10.1016/j.ecosys.2012.02.002
Lee C-C, Chen M-P (2020) The impact of COVID-19 on the travel and leisure industry returns: some international evidence. Tour Econ 28(2):451–472. https://doi.org/10.1177/1354816620971981
Lee M, Song JW, Park JH, Chang W (2017) Asymmetric multi-fractality in the U.S. stock indices using index-based model of A-MFDFA. Chaos Solitons Fractals 97:28–38. https://doi.org/10.1016/j.chaos.2017.02.001
Lee Y-J, Kim N-W, Choi K-H, Yoon S-M (2020) Analysis of the informational efficiency of the EU carbon emission trading market: asymmetric MF-DFA approach. Energies 13(9):2171. https://doi.org/10.3390/en13092171
Levich R, Conlon T, Poti V (2019) Measuring excess-predictability of asset returns and market efficiency over time. Econ Lett 175:92–96. https://doi.org/10.1016/j.econlet.2018.12.022
Li J, Miller NC (2015) Foreign exchange market inefficiency and exchange rate anomalies. J Int Financ Markets Inst Money 34:311–320. https://doi.org/10.1016/j.intfin.2014.12.001
Liu HY, Manzoor A, Wang CY, Zhang L, Manzoor Z (2020a) The COVID-19 outbreak and affected countries stock markets response. Int J Environ Res Public Health 17(8):2800. https://doi.org/10.3390/ijerph17082800
Liu L, Wang EZ, Lee CC (2020b) Impact of the COVID-19 pandemic on the crude oil and stock markets in the US: a time-varying analysis. Energy Res Lett 1(1):1–5. https://doi.org/10.46557/001c.13154

Lu X, Tian J, Zhou Y, Li Z (2013) Multifractal detrended fluctuation analysis of the Chinese stock index futures market. Physica A Stat Mech Appl 392(6):1452–1458. https://doi.org/10.1016/j.physa.2012.11.037
Ma Y, Wang Z, He F (2020) How do economic policy uncertainties affect stock market volatility? Evidence from G7 countries. Int J Finance Econ 27(2):2303–2325. https://doi.org/10.1002/ijfe.2274
MacDonald R, Taylor MP (1992) Exchange rate economics: a survey. IMF Staff Pap 39(1):1–57. https://doi.org/10.2307/3867200
Mandelbrot BB (1967) The variation of some other speculative prices. J Bus 40(4):393–413
Mandelbrot BB (1972) Possible refinements of the lognormal hypothesis concerning the distribution of energy dissipation in intermittent turbulence. In: Rosenblatt M, van Atta C (eds) Statistical Models and Turbulence. Springer, Berlin, pp 333–351
Mandelbrot BB (1974) Intermittent turbulence in self similar cascades: divergence of high moments and dimension of the carrier. J Fluid Mech 62(2):331–358. https://doi.org/10.1017/S0022112074000711
Mandelbrot BB (1975) Stochastic models for the earth's relief, the shape and the fractal dimension of the coastlines, and the number area rule for Islands. Proc Natl Acad Sci USA 72(10):3825–3828
Mandelbrot BB (1997) The variation of the prices of cotton, wheat, and railroad stocks, and of some financial rates. Fractals and Scaling in Finance. Springer, Berlin, pp 419–443
Mandelbrot BB, van Ness JW (1968) Fractal Brownian motions, fractal noises and applications. SIAM Rev 10(4):422–437
Mandelbrot BB, Fisher A, Calvet L (1997) A multifractal model of asset returns. *Cowles Foundation Discussion Papers*, 1164. Cowles Foundation for Research in Economics, Yale University
Mazur M, Dang M, Vega M (2021) COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. Finance Res Lett 38:101690. https://doi.org/10.1016/j.frl.2020.101690
Mehrara M, Oryare AR (2012) Efficient market hypothesis in foreign exchange market before and after the global financial crisis of 2007-08. Int J Bus Soc Sci 3(9):165–167
Miloş LR, Hatiegan C, Miloş MC, Barna FM, Botoc C (2020) Multifractal detrended fluctuation analysis (MF-DFA) of stock market indexes: empirical evidence from seven central and Eastern European markets. Sustainability 12(2):535. https://doi.org/10.3390/su12020535
Mnif E, Jarboui A (2021) COVID-19, bitcoin market efficiency, herd behavior. Rev Behav Finance 13(1):69–84. https://doi.org/10.1108/RBF-09-2020-0233
Mnif E, Jarboui A, Mouakhar K (2020) How the cryptocurrency market has performed during COVID 19? A multifractal analysis. Finance Res Lett 36:101647. https://doi.org/10.1016/j.frl.2020.101647
Mobarek A, Mollah S, Keasey K (2014) A cross-country analysis of herd behavior in Europe. J Int Financ Mark Inst Money 32:107–127. https://doi.org/10.1016/j.intfin.2014.05.008
Narayan PK (2020) Did bubble activity intensify during COVID-19? Asian Econ Lett 1(2). https://doi.org/10.46557/001c.17654
Narayan PK, Phan DHB, Liu G (2021) COVID-19 lockdowns, stimulus packages, travel bans, and stock returns. Finance Res Lett 38:101732. https://doi.org/10.1016/j.frl.2020.101732
Ning Y, Han C, Wang Y (2018) The multifractal properties of Euro and pound exchange rates and comparisons. Physica A 509:578–587. https://doi.org/10.1016/j.physa.2018.06.037
OECD (2020) Global financial markets policy responses to COVID-19. OECD Publishing, Paris
Özdemir O, Kumar AS (2024) Dynamic efficiency and herd behavior during pre- and post-COVID-19 in the NFT market: evidence from multifractal analysis. Comput Econ 63:1255–1279. https://doi.org/10.1007/s10614-023-10522-z
Peng CK, Buldyrev S, Havlin S, Simons M, Stanley HE, Goldberger A (1994) Mosaic organization of DNA nucleotides. Phys Rev E 49(2):1685–1689. https://doi.org/10.1103/PhysRevE.49.1685
Peters E (1991) Chaos and order in the capital markets: A new view of cycles, prices and market volatility. John Wiley & Sons, New York
Peters E (1994) Fractal market analysis: Applying chaos theory to investment and economics. John Wiley & Sons, New York
Phillips PCB, Shi S-P (2018) Financial bubble implosion and reverse regression. Econ Theory 34(4):705–753. https://doi.org/10.1017/S0266466617000202
Phillips PCB, Shi S-P (2020) Real time monitoring of asset markets: Bubbles and crises. In: Vinod HD, Rao CR (eds) Handbook of Statistics: Financial, Macro and Micro Econometrics Using R. Elsevier, Amsterdam, pp 61–80
Phillips PCB, Wu Y, Yu J (2011) Explosive behavior in the 1990s nasdaq: when did exuberance escalate asset values? Int Econ Rev 52(1):201–226. https://doi.org/10.1111/j.1468-2354.2010.00625.x

Phillips PCB, Shi S-P, Yu J (2015) Testing for multiple bubbles: historical episodes of exuberance and collapse in the S&p 500. Int Econ Rev 56(4):1043–1078. https://doi.org/10.1111/iere.12132
Ramelli S, Wagner AF (2020) Feverish stock price reactions to COVID-19. Rev Corp Financ Stud 9(3):622–655. https://doi.org/10.1093/rcfs/cfaa012
Rapp TA, Sharma SC (1999) Exchange rate market efficiency: across and within countries. J Econ Bus 51(5):423–439. https://doi.org/10.1016/S0148-6195(99)00017-X
Rizvi SAR, Arshad S (2016) How does crisis affect efficiency? An empirical study of East Asian markets. Borsa Istanb Rev 16(1):1–8. https://doi.org/10.1016/j.bir.2015.12.003
Rizvi SAR, Dewandaru G, Bacha OL, Masih M (2014) An analysis of stock market efficiency: developed vs Islamic stock markets using MF-DFA. Physica A: Statistical Mechanics and its Applications 407:86–99. https://doi.org/10.1016/j.physa.2014.03.091
Salisu AA, Akanni L, Raheem I (2020) The COVID-19 global fear index and the predictability of commodity price returns. J Behav Exp Finance 27:100383. https://doi.org/10.1016/j.jbef.2020.100383
Samuelson PA (1965) Proof that properly anticipated prices fluctuate randomly. Ind Manage Rev 6(2):41–49
Sansa NA (2020) The impact of the COVID-19 on the financial markets: evidence from China and USA. Electron Res J Soc Sci Humanit 2(2):29–39
Sewell M (2011) History of the efficient market hypothesis. UCL Res Note, 1–14
Sha Y, Sharma SS (2020) Research on pandemics special issue of the journal emerging markets finance and trade. Emerg Mark Finance Trade 56(10):2133–2137. https://doi.org/10.1080/1540496X.2020.1795467
Shahzad SJH, Hernandez JA, Hanif W, Kayani GM (2018) Intraday return inefficiency and long memory in the volatilities of forex markets and the role of trading volume. Physica A 506:433–450. https://doi.org/10.1016/j.physa.2018.04.016
Sharma SS (2020) A note on the Asian market volatility during the COVID-19 pandemic. Asian Econ Lett 1(2):1–6. https://doi.org/10.46557/001c.17661
Sharma GD, Tiwari AK, Jain M, Yadav A, Erkut B (2021) Unconditional and conditional analysis between COVID-19 cases, temperature, exchange rate and stock markets using wavelet coherence and wavelet partial coherence approaches. Heliyon 7(2):e06181. https://doi.org/10.1016/j.heliyon.2021.e06181
Su ZY, Wang YT, Huang HY (2009) A multifractal detrended fluctuation analysis of taiwan's stock exchange. J Korean Phys Soc 54(4):1395–1402. https://doi.org/10.3938/jkps.54.1395
Takahashi H, Yamada K (2021) When the Japanese stock market meets COVID-19: impact of ownership, China and US exposure, and ESG channels. Int Rev Financ Anal 74:101670. https://doi.org/10.1016/j.irfa.2021.101670
Tan ÖF (2021) The effect of pandemic news on stock market returns during the COVID-19 crash: evidence from international markets. Istanbul Univ J Commun Sci 60:217–240. https://doi.org/10.26650/CONNECTIST2021-884955
Tetlock P (2007) Giving content to investor sentiment: the role of media in the stock market. J Finance 62(3):1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x
Tiwari AK, Aye GC, Gupta R (2019) Stock market efficiency analysis using long spans of data: a multifractal detrended fluctuation approach. Finance Res Lett 28:398–411. https://doi.org/10.1016/j.frl.2018.06.012
Wong YM, Ahmad R (2013) Foreign exchange markets efficiency under recent crises: Evidence from the European markets. *European Financial Management Association 2013 Annual Meeting*, At: University of Reading, UK
Worthington AC, Higgs H (2006) Weak-form market efficiency in Asian emerging and developed equity markets: comparative tests of random walk behaviour. Acc Res J 19(1):54–63
Wu G, Yang B, Zhao N (2020) Herding behavior in Chinese stock markets during COVID-19. Emerg Markets Finance Trade 56(15):3578–3587. https://doi.org/10.1080/1540496X.2020.1855138
Yan C (2020) Outbreak and stock prices: Evidence from China. *SSRN Electronic Journal*, Available at SSRN: https://ssrn.com/abstract=3574374
Yuan Y, Zhuang X-t, Jin X (2009) Measuring multifractality of stock price fluctuation using multifractal detrended fluctuation analysis. Physica A Stat Mech its Appl 388(11):2189–2197. https://doi.org/10.1016/j.physa.2009.02.026
Zaremba A, Kizys R, Aharon DY, Demir E (2020) Infected markets: novel coronavirus, government interventions, and stock return volatility around the globe. Finance Res Lett 35:101597. https://doi.org/10.1016/j.frl.2020.101597

Zhang D, Hu M, Ji Q (2020) Financial markets under the global pandemic of COVID-19. Finance Res Lett 36:101528. https://doi.org/10.1016/j.frl.2020.101528

Zunino L, Tabak BM, Figliola A, Pérez DG, Garavaglia M, Rosso OA (2008) A multifractal approach for stock market inefficiency. Physica A 387(26):6558–6566. https://doi.org/10.1016/j.physa.2008.08.028

Zunino L, Figliola A, Tabak BM, Pérez DG, Garavaglia M, Rosso OA (2009) Multifractal structure in Latin-American market indices. Chaos Solitons Fractals 41(5):2331–2340. https://doi.org/10.1016/j.chaos.2008.09.013