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# Disentangling the impact of economic and health crises on financial markets

Aurelio F. Bariviera [a], Laura Fabregat-Aibar [b], Maria-Teresa Sorrosal-Forradellas [b,*]

[a] *Universitat Rovira i Virgili, Department of Business Management, ECO-SOS, Av. Universitat 1, 43204 Reus, Spain*
[b] *Universitat Rovira i Virgili, Department of Business Management, Av. Universitat 1, 43204 Reus, Spain*

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ABSTRACT

This paper explores the impact of different crises on the informational efficiency of financial assets. The study covers stock markets indices (ASX200, DAX30, EuroStoxx50, S&P500 and Nikkei), commodities (gold and oil) and volatility (VIX). The study analyzes, using a rolling window method, the long memory profile and the multifractality of the time series by means of the DFA and generalized Hurst exponents. This dynamic analysis is important as it uncovers the time-varying behavior of returns characteristics, affecting the investment decisions and trading strategies at different moments of time. The paper extends the current literature on informational efficiency, providing evidence of the distinct impact on the long memory and on the multifractality of the time series, depending on the nature of the crisis and the market. The results could be of interest for investors as well as for academics, regarding the hedging limits of the models during calm or turbulent times.

## 1. Introduction

The Efficient Market Hypothesis (EMH) constitutes the standard benchmark model for the ideal behavior of price changes in a competitive market. The first statistical model was proposed by Bachelier (1900), who developed an arithmetic Brownian motion setup in order to price French government bonds futures. Theoretical developments in asset pricing remained in latency until the 1950s and 1960s, with the formalization of modern portfolio theory (Markowitz, 1952), one factor asset pricing theory (Sharpe, 1964; Lintner, 1965; Mossin, 1966), and finally with the adoption of the geometric Brownian motion as the standard model (Osborne, 1959, 1962; Samuelson, 1965).

Fama (1965) captures the *zeitgeist* of financial economics at that time, reflecting the empirical validity of the random walk model. However, empirical tests in subsequent decades showed some limits of the geometric Brownian motion as a model able to embrace all markets under any situation. In particular, when markets are under stress market participants behave differently. Under such circumstances, anomalous behavior emerges (Bariviera et al., 2014).

The recent Covid-19 pandemic offers the possibility to study a rare, unforeseeable event. Its nature differs from the other crises such as the dot-com crisis around year 2000, the 2008 financial crisis, or the European debt crisis. Despite its different origin, Covid-19 has had important economic consequences. Thus, it is worth investigating if all crises affected similarly the stochastic dynamics of financial markets or whether the impact was different depending on the nature of each crisis.

Unlike previous literature (Cajueiro et al., 2009; Kim et al., 2011; Martinez et al., 2018; Fernandes et al., 2021), which study the effect of a single crisis on the informational efficiency in some financial markets, the current paper addresses a more comprehensive

* Corresponding author.
*E-mail addresses:* aurelio.fernandez@urv.cat (A.F. Bariviera), laura.fabregat@urv.cat (L. Fabregat-Aibar), mariateresa.sorrosal@urv.cat (M.-T. Sorrosal-Forradellas).

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approach. Particularly, it covers more than two decades of data under different political and economic situations. The period under analysis includes important events such as the dot-com crash, the 2008 global financial crisis or the more recent Covid-19 pandemic. Moreover, the financial assets under scrutiny are not only the main stock market indices, but also important commodities (Gold and Oil) and a volatility index (VIX).

The aim of this paper is to detect specific stochastic signatures of the effect of different type of crises in the time series of financial assets. Using a rolling window procedure to analyze long memory and multifractality, it is possible to unveil the time-varying characteristics of the financial returns. Such approach could be of interest for investors, as it gives hints on the timing of trading strategies.

The paper contributes to the literature in several aspects. First, it studies the stochastic behavior of different financial assets (from diverse geographical zones and characteristics) covering the last two decades, from the dot-com bubble up to the recent Covid-19 pandemic. Second, the long memory and multifractality of the time series using different time windows are analyzed. Third, results unveil uneven impacts in the different financial assets due to either economic, financial or health crises.

The remaining of the paper is organized as follows: Section 2 presents a literature review, Section 3 briefly describes the quantitative methodologies used in the paper; Section 4 describes the data used and Section 5 discusses the main findings. Finally, Section 6 draws the main conclusions.

## 2. Literature review

According to the EMH, asset prices fully reflect all available information (Fama, 1976). Therefore, investors cannot obtain, on a regular basis, superior returns based on the analysis of past information, as it is already embedded into current prices. In other words, this financial theory assumes that information flow toward financial markets is inexorable: market participants cannot control its arrival and it will be reflected in prices immediately. As a consequence, the behavior of price time series will follow a random walk.

The EMH remained unchallenged until the late 1970s, when empirical studies begin to cast doubts upon its validity. It is worth to mention that a special issue of the Journal of Financial Economics published in 1978, dedicated exclusively to market anomalies, marked a turning point in the literature. According to Keane (1986), the fact that this journal devoted a special issue to anomalies led more researchers to dedicate themselves to this topic and accelerated the amount of evidence against EMH.

In line with the Adaptive Market Hypothesis, proposed by Lo (2004), several studies analyze the time-varying behavior of market efficiency. Ito and Sugiyama (2009) conclude that inefficiency varies over time in the US stock market. Cajueiro et al. (2009) find that information efficiency in the Greek Stock market increases with the liberalization of the financial market. Bariviera (2011) finds long-range dependence in the Thai Stock market weakly influenced by the liquidity level and market size. Kim et al. (2011) observe that return predictability of the Dow Jones Industrial Average index from 1900 to 2009 is altered by political and economic crises but not market crises. Bariviera et al. (2014) study the impact of the 2008 financial crisis on fifteen European sectorial indices of corporate bonds. They use Hurst exponent to analyze the time-varying behavior of long-range memory and find that the financial crisis has uneven effects on the informational efficiency of corporate bonds. Zheng et al. (2018) applied the modified R/S analysis of Lo (1991) to different stock markets indices (S&P 500 index, CSI 300 index and DAX 30) finding that the speed of the price adjustment has an impact on the long memory of volatility.

More recently, os et al. (2021), studying the stylized facts of hedge funds and foreign exchange markets, find that daily data also presents similar characteristics to other inefficient markets such as fat-tails, volatility clustering, and long memory in volatility. Ozkan (2021) investigates the impact of Covid-19 on stock markets efficiency using the MF-DFA method in six of the most-hard hit countries by the disease: US, Spain, UK, Italy, France and Germany. The results show the inefficiency of these countries in some periods during the pandemic, as stock markets became more speculative. In this line, Fernandes et al. (2021) also find that the Covid-19 crisis caused inefficiency in most equity sectors in China. Finally, Arouxet et al. (2022) report that Covid-19 pandemic, albeit producing a mild effect on the long memory of cryptocurrency returns, triggered a temporary severe impact in the long memory of volatility.

## 3. Methodology

### 3.1. The Hurst exponent

The British hydrologist H.E. Hurst proposed a method to detect and measure long-range dependence (Hurst, 1951, 1956). The R/S analysis is defined as the range of the partial sums of deviations of a time series with respect to its mean, rescaled by its standard deviation. This analysis was first applied to long term behavior of water reservoirs, but afterwards it was employed to the analysis of economical time series, introduced by Mandelbrot (1972). At the beginning of the 1990s, Lo (1991) proposed an improvement of the R/S analysis.

Considering a time series of prices $\{P_t\}$, with $t = 1, 2, \ldots, M+1$ of an asset, the transformed series $\{R_t\}$ with $t = 1, 2, \ldots, M$, such that $R_t = ln\frac{P_{t+1}}{P_t}$, is the continuous return of the asset. In order to obtain the R/S statistic, the new series $\{R_t\}$ is divided in a set of $A$ periods of length $N$. For each of these $N$-periods, the range of the partial sums of deviations is obtained in the following way:

$$R_{i,N} = \max_{1\leq k\leq N}\left(x_{i,N,k}\right) - \min_{1\leq k\leq N}\left(x_{i,N,k}\right) \text{ with } i = 1, 2, \ldots, A \tag{1}$$

where $x_{i,N,k} = \sum_{j=1}^{k} \left( x_{i,j} - \mu_{i,N} \right)$ is a measure of the cumulative distance between each observation and the mean of the period, being $\mu_{i,N}$ the arithmetic mean of the values of $\{R_t\}$ in the $i$th period of length $N$.

For comparison reasons, this range is divided by the standard deviation

$$S_{i,N} = \left[ \frac{1}{N} \sum_{j=1}^{n} \left( x_{i,j} - \mu_{i,N} \right)^2 \right]^{\frac{1}{2}} \tag{2}$$

The $R/S$ statistic, for each value of $N$, is then calculated as follows:

$$(R/S)_N = \sum_{i=1}^{A} \left( \frac{R_{i,N}}{S_{i,N}} \right) \tag{3}$$

Note that the $R/S$ statistic is always positive, because the numerator (a range) as well as the denominator (a standard deviation) are always positive.

The relationship between the $R/S$ statistic and the length $N$ is given by $\left(\frac{R}{S}\right)_N = \alpha \cdot N^H$, where $\alpha$ is a constant and $H$ is the Hurst exponent. If $H = 0.5$, the time series $\{R_t\}$ has no memory. If $H \in (0,\ 0.5)$ the series is anti-persistent or mean-reverting, and if $H \in (0.5, 1)$ the series is persistent.

### 3.2. Detrended Fluctuation Analysis

The main drawback that presents the $R/S$ analysis developed by Hurst is that it can be affected by short term dependence (Lo, 1991; Grau-Carles, 2000). To avoid this inconvenient, Peng et al. (1994) proposed the Detrended Fluctuation Analysis (DFA). Some authors (Pilgram and Kaplan, 1998; Hu et al., 2001) show that DFA has a better performance that R/S analysis. Another research line advocates for the use of the Detrended Moving Average (DMA) technique (Madani et al., 2020; Ftiti et al., 2021; Madani and Ftiti, 2022) because such approach does not require partitioning the series under analysis into non-overlapping sections. However, Shao et al. (2012) benchmarking different long run methods, find that DFA is not as good as DMA only in some situations and report that both DFA and DMA are the best methods for estimating the Hurst exponent. Consequently, in this paper DFA is applied. This analysis has been used previously in other papers to examine the memory of different financial assets, for instance, European corporate bonds and stock markets (Martinez et al., 2018), crude oil markets (Alvarez-Ramirez et al., 2008; Wang and Liu, 2010), spot and futures energy markets (Khediri and Charfeddine, 2015), among others.

The DFA algorithm could be described as follows:

1. The first step in this analysis consists in computing the mean of a stochastic time series $y(t)$ with $t = 1, 2, \dots, M$, noted as $\bar{y} = \frac{1}{M} \cdot \sum_{t=1}^{M} y(t)$. Next, the integrated time series $x(i)$ with $i = 1, 2, \dots, M$ is obtained as $x(i) = \sum_{t=1}^{i} y(t) - \bar{y}$.
2. In a second step, the time series $x(i)$ is divided into non overlapping subsamples of size $m$.
3. In a third stage, the trend of each subsample is determined using $z_p(i, m)$, a polynomial fit of order $p$. The fluctuation function $F(m)$ is computed using the expression:

$$F(m) = \sqrt{\frac{1}{M} \sum_{i=1}^{M} \left[ x(i) - z_p(i, m) \right]^2} \tag{4}$$

4. Finally, the previous steps are repeated using different values of $m$.

Peng et al. (1994) recommended to use values of $m$ between 5 (a size smaller than 5 can produce deterministic components) and $M/5$ (a size larger than $M/5$ can produce that $F(m)$ does not follow a power-law scaling behavior). If $F(m)$ behaves as a power-law of $m$, then $F(m) \propto m^H$, being $H$ the aforementioned Hurst exponent, that can be obtained as the slope of $\ln(F(m))$ onto $\ln(m)$ using the different values of $(m, F(m))$ found previously.

#### 3.2.1. Randomness test

When analyzing financial time series, one of the goals is to test whether or how close to a random process a given series is. Usually, the computation of the Hurst exponent (and other metrics of randomness) is performed on relatively small size samples. In this paper, sliding windows of 250 observations are considered. As a consequence of the finite size, Brownian motion samples could give a value $H \neq 0.5$, even in the absence of long memory. Thus, it becomes necessary to estimate confidence intervals for the Hurst estimates. In order to do so, random surrogates for each window are generated, which destroys any linear correlation in it, while preserving its amplitude. Then, the Hurst exponent of such surrogates is computed, obtaining their mean and standard error, and constructing the confidence interval. The 99% confidence level is shown as a dark gray area in Fig. 1.

### 3.3. The generalized Hurst exponent

Following Di Matteo et al. (2003), the long-memory framework proposed could be expanded to higher moments of the distribution of price changes. Such elaboration unveils additional properties of time series. Let consider the first $q$-order moments of the distribution of absolute price changes

$$K_q(\tau) = \mathbb{E}\left[ |\ln(P(t+\tau)) - \ln(P(t))|^q \right] \cdot \mathbb{E}\left[ |\ln(P(t))|^q \right] \tag{5}$$

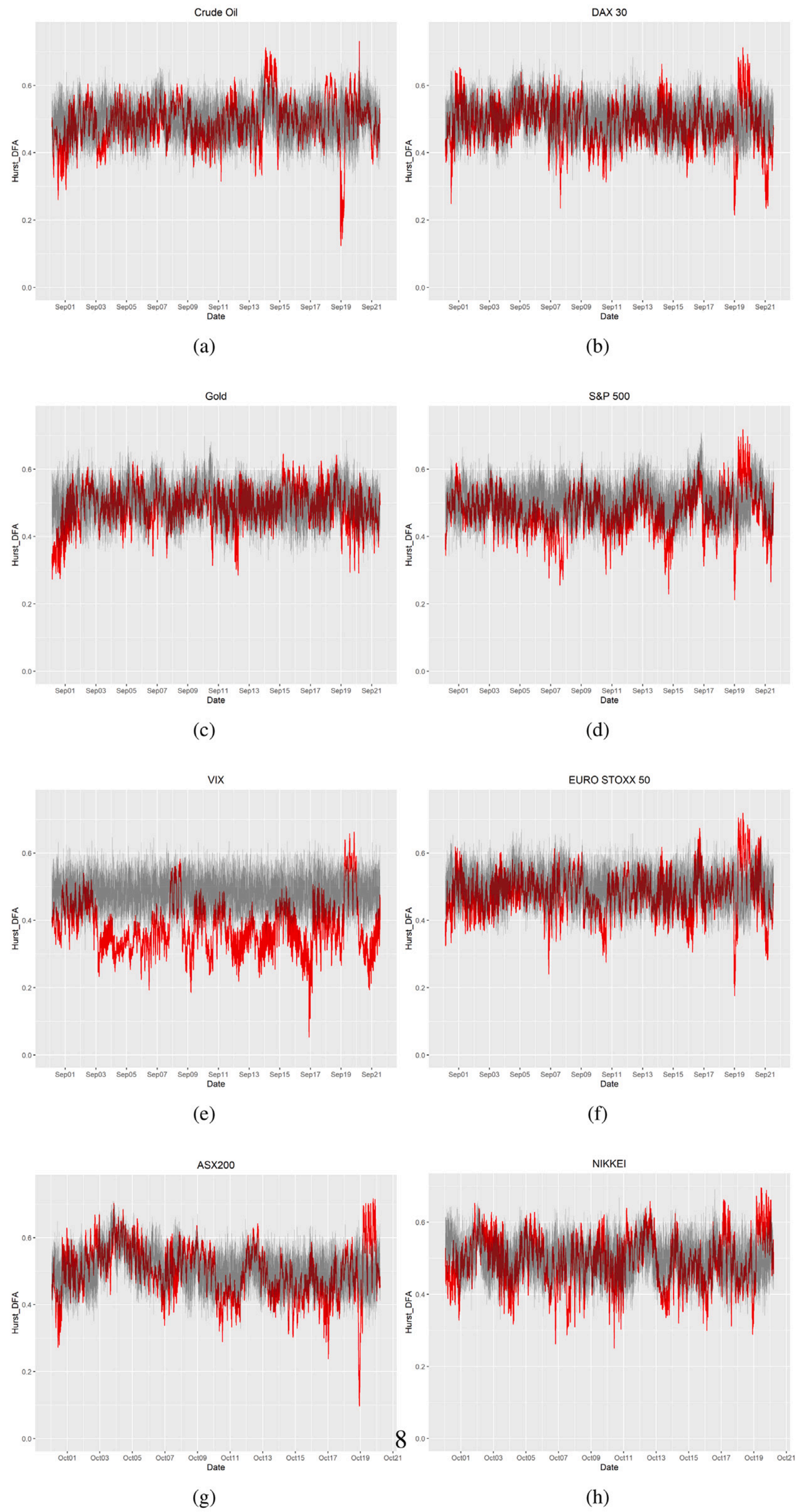


**Fig. 1.** Hurst exponent estimates of the daily returns of each time series, using rolling window of 250 observations. Dark gray shaded area is the 99% confidence interval.

**Table 1**
Descriptive statistics of the DFA Hurst exponents of daily returns.

| | Gold | Crude oil | VIX | S&P500 | DAX30 | EuroStoxx50 | ASX200 | NIKKEI |
|---|---|---|---|---|---|---|---|---|
| Observations | 4908 | 4908 | 4908 | 4908 | 4908 | 4908 | 4908 | 4908 |
| Mean | 0.4860 | 0.4887 | 0.3742 | 0.4729 | 0.4841 | 0.4762 | 0.4921 | 0.4842 |
| Median | 0.4893 | 0.4892 | 0.3649 | 0.4749 | 0.4858 | 0.4771 | 0.4945 | 0.4843 |
| Min | 0.2730 | 0.1240 | 0.0532 | 0.2119 | 0.2147 | 0.1758 | 0.0969 | 0.2490 |
| Max | 0.6454 | 0.7310 | 0.6627 | 0.7178 | 0.7127 | 0.7190 | 0.7171 | 0.6942 |
| Std. Deviation | 0.0569 | 0.0678 | 0.0756 | 0.0643 | 0.0647 | 0.0648 | 0.0784 | 0.0650 |
| Skewness | −0.5169 | −0.5361 | 0.5062 | −0.1710 | −0.3615 | −0.1006 | −0.3761 | −0.0707 |
| Kurtosis | 3.5720 | 5.6692 | 3.8102 | 3.7968 | 4.0544 | 4.1764 | 3.7610 | 2.9802 |
| Jarque Bera | 284.5463 | 101.4499 | 101.5686 | 240.6510 | 50.6854 | 81.2525 | 49.3962 | 7.9713 |

where $\mathbb{E}(\cdot)$ is the expectation operator. Then, the generalized Hurst exponent $H(q)$ arises from the scaling behavior of $K_q(\tau)$ as:

$$K_q(q) \propto \tau v^{q \cdot H(q)} \tag{6}$$

Processes where $H(q) = H$, i.e. $H$ is constant and independent of $q$, are called monofractal. Meanwhile, multifractal processes are those where the scaling of the first $q$ moments, defined in Eq. (5), scales non-linearly with $q$. One straightforward way to discriminate mono and multifractal processes is to produce a planar representation $q \times qH(q)$. Monofractal processes such as standard and fractional Brownian motions produce a straight line, whose slope depends on the value of the Hurst exponent. However, the line produced by multifractal processes bends downward, providing a clear signature of deviations from the theoretical Brownian motion.

## 4. Data

This paper uses closing daily values of the following commodities and indices: gold, crude oil, VIX, S&P500, DAX30, EuroStoxx50, ASX200, and Nikkei. Data were obtained from Eikon Thomsom Reuters, and covers from  April 2000 until September 2022, for a total of 5157 observations.

## 5. Results and discussion

The empirical analysis encompasses two analysis. First, the paper studies dynamically the evolution of the long memory of the different time series, by means of the DFA Hurst exponent. Second, it analyzes the multifractality using the generalized Hurst exponent. Table 1 displays the descriptive statistics of the Hurst exponents of daily returns of all assets.

In order to detect the evolution of the long memory, the Hurst exponent is computed using sliding windows. The rolling sample approach works as follows: the Hurst's exponent is computed for the first 250 logarithmic returns, then the first return is discarded and the following return of the time series is added, and continue this way until the end of data. Thus, each $H$ estimate is calculated from data samples of the same size.

It is detected that, in line with previous studies (Cajueiro et al., 2009; Bariviera et al., 2014), long memory is not constant (see Fig. 1). However its variation is heterogeneous in the time series under study. Different financial assets are affected dissimilarly by events such as financial or political crises.

A common feature of most time series is the period in which the maximum and minimum values of the Hurst exponent ($H$) were reached. For the DAX30, S&P500, EuroStoxx50 and ASX200 indices, as well as for Crude Oil, the minimum $H$ is found at the beginning of the Covid-19 pandemic, while the maximum values are observed some months later, when the disease began to be controlled by vaccines. These values, far from $H = 0.5$, reveal that these markets become more inefficient with the health crisis.

The maximum value of $H$ for NIKKEI was also reached in the aftermath of the pandemic, but the minimum value in the Japanese market is found during 2011, around the months when the tsunami on the Honshu Island occurred.

Since gold is commonly considered a safe-haven asset, the evolution of its $H$ values is quite different from the rest. Although the exponents decreased during the Covid-19 pandemic, the minimum took place in a window that includes the dot-com crisis and the maximum value was reached in 2016, contemporaneous to the Brexit referendum. However, the mean of the Hurst exponent for gold is the closest to 0.5 and wanders mostly within the 99% confidence level, thus being the most efficient of all the assets analyzed in this study.

Regarding VIX, its behavior is clearly different from the rest of assets. Although the maximum Hurst exponent for VIX is also in a window related to the Covid-19 crisis, its minimum was reached during the second half of 2017, coinciding with a period of low market volatility. It is noteworthy that the $H$ value takes a value lower than 0.5 in almost all the period and an average below 0.4, indicating VIX follows a mean-reverting process. This fact is due to the nature of the index, since it measures the volatility of the market and it is used to hedge such volatility.

It is important to highlight the relationship between the value of $H$ and the efficiency of the market, including the implications for investors. When $H = 0.5$, the market can be considered informationally efficient and, consequently, it would be meaningless for investors to engage in any trading strategy because returns behave as a random walk. Although the mean of all the assets (except VIX) is close to this value, it is observed in Table 1 that there are periods when $H$ is higher than 0.5 (the maximum ranges between 0.6454 for gold and 0.7310 for crude oil) and others when it is lower (the minimum varies between 0.0532 for VIX and 0.2730 for gold) where the market is clearly inefficient. Precisely in such periods investors can take advantage of market inefficiency. When $H > 0.5$ the market is persistent, so investors can exploit the fact that increases (decreases) will be more likely followed by increases (decreases). During the Covid-19 pandemic, the assets mainly showed a persistent behavior that can be explained by a herd effect. When $H < 0.5$ the process is mean-reverting, which indicates that increases in the time series will be more likely followed by decreases and vice versa. This situation was found after the Covid-19 crisis, where the assets experimented a mean-reverting process. Thus, contrarian or follow-the-market investment strategies could be profitable under the previous described inefficiency situations. The intensity of the efficiency or inefficiency of an asset can be measured, following Ftiti et al. (2021), with the efficiency index, defined as the difference, in absolute value, between its $H$ and the value 0.5.

An alternative look on the time-varying efficiency can be observed computing the generalized Hurst exponent. As explained in Section 3, if the time series follows a standard Brownian motion (i.e., if it is monofractal), the Hurst exponent scales linearly with $q$. Therefore, the planar representation $q \times q \cdot H(q)$ provides visual evidence for the existence of multifractality. In this section of the work each time series is studied in non-overlapping windows of 250 observations, comprising each window approximately one trading year. The reason for the selection of the length is twofold: (i) it is sufficient to provide a robust estimation of the Hurst exponent; (ii) it allows to split the series and isolate the effect of the events occurred during such window.

The analysis shows that, for most of the years under study, the time series exhibit mild symptoms of multifractality. The exceptions are the years with different crises. However, not all crises affect financial assets in the same way. Regarding the crude oil, the greatest departure from monofractality is detected in years 2001 and 2008, contemporaneous of the 9/11 attack against the World Trade Center complex in New York and the Global Financial Crisis (GFC), respectively. It is also observed that, to a lesser extent, years 2011 and 2012 exhibit multifractality (corresponding to the end of the GFC and the European debt crisis). Moreover, it is detected that Covid-19 had also a moderate effect in the behavior of this time series.

The S&P500 index displays the closest monofractal behavior, among the time series of the sample. The most remarkable incidence of multifractality is found in years 2008 (GFC), 2012 (European debt crisis) and 2016. This last year was remarkable in terms of multifractality because in addition to S&P500, also DAX30, VIX and NIKKEI show multifractal behavior during this year, and a little earlier for EuroStoxx50. The crisis over the Brexit referendum in 2016 and the notification in 2017 of UK to the European Council to leave the European Union may be a possible explanation for it.

Regarding gold, the most multifractal behavior is displayed in the period 2001–2002, the same period in which gold moves away from efficiency with values of $H$ below 0.5. Covid-19 effect on financial markets deserves a special analysis. In all the time series under scrutiny (except crude oil), the pandemic cannot be associated with multifractal dynamics. It is clear that the effect in returns and volatility (and in long memory as seen in Fig. 1) were significant. However, and unlike other events (9/11, GFC, European debt crisis, Brexit), which shaked the pillars of market behavior, Covid-19 did not affect the monofractality of the time series. It can be seen in Fig. 2, that for all time series but crude oil, the generalized Hurst exponent during 2020 scales (quasi)linearly with $q$ and lies above the straight line that represents the Hurst exponent of a simulated Brownian motion with $H = 0.5$. This result signalizes that during this period $H > 0.5$ and its behavior is approximately monofractal.

Fig. 3 displays the $q \times q \cdot H(q)$ plane for the shuffled returns within each window. The rationale for working with this surrogate time series is detecting the origin of multifractality. Kantelhardt et al. (2002) explains that there are two sources of multifractality: one is connected with the probability density function form, and the other is linked with the long-range correlation framework. Shuffling the time series dismantle non-trivial correlations, uncovering if multifractality is due to the correlation setting. On contrary, if multifractality is due to the probability distribution (e.g. fat tails), randomizing the time series will not (mainly) modify the original results. If both sources of multifractality are present in the time series, shuffling will only reduce the multifractal signature. In this case, it is observed in Fig. 3 that the multifractality signature is present in the corresponding surrogate series. Moreover, in order to quantify the source of multifractality, the width of the multifractal spectrum ($\alpha$) is calculated using the Matlab routine developed by Ihlen (2012). The use of the difference between $\alpha_{max}$ and $\alpha_{min}$ to show the changes in multifractality was also used in Ftiti et al. (2021). As displayed in Table 2, the original series present a mean value of this difference near to 0.40. In order to detect the source of multifractality, two procedures are undertaken. First the original time series (within each window) are shuffled, and second Brownian motions are simulated. This analysis detects that the shuffling procedure obtains lower values of the multifractal spectrum width (around 0.35), as displayed in Table 3. Nevertheless, those values are greater than those expected by a standard Gaussian noise.[1] Thus, it can be concluded that multifractality stems from both, the probability density distribution (in particular, fat tails) as well as the presence of long memory in the original series. As the EMH lays down on a monofractal model, it is important that investors take into account the multifractality of the series in their investment decisions. The notion of multifractality entails that there is different values of $H$ for different scales, so, the behavior in terms of efficiency and inefficiency (persistent or mean-reverting) can be different in the short, middle and long run. Consequently, investors should consider not a single value of $H$ but the $H$ that corresponds to their investment horizon.

[1] The Matlab function `wfbm` was used to generate 50 independent simulations of 5157 observations each one. Then, first differences are computed in order to obtain the corresponding Gaussian noises. Subsequently, the multifractality spectrum width was computed for non-overlapping windows of 250 observations. The mean of such simulations was 0.2553 with a standard deviation of 0.0221.

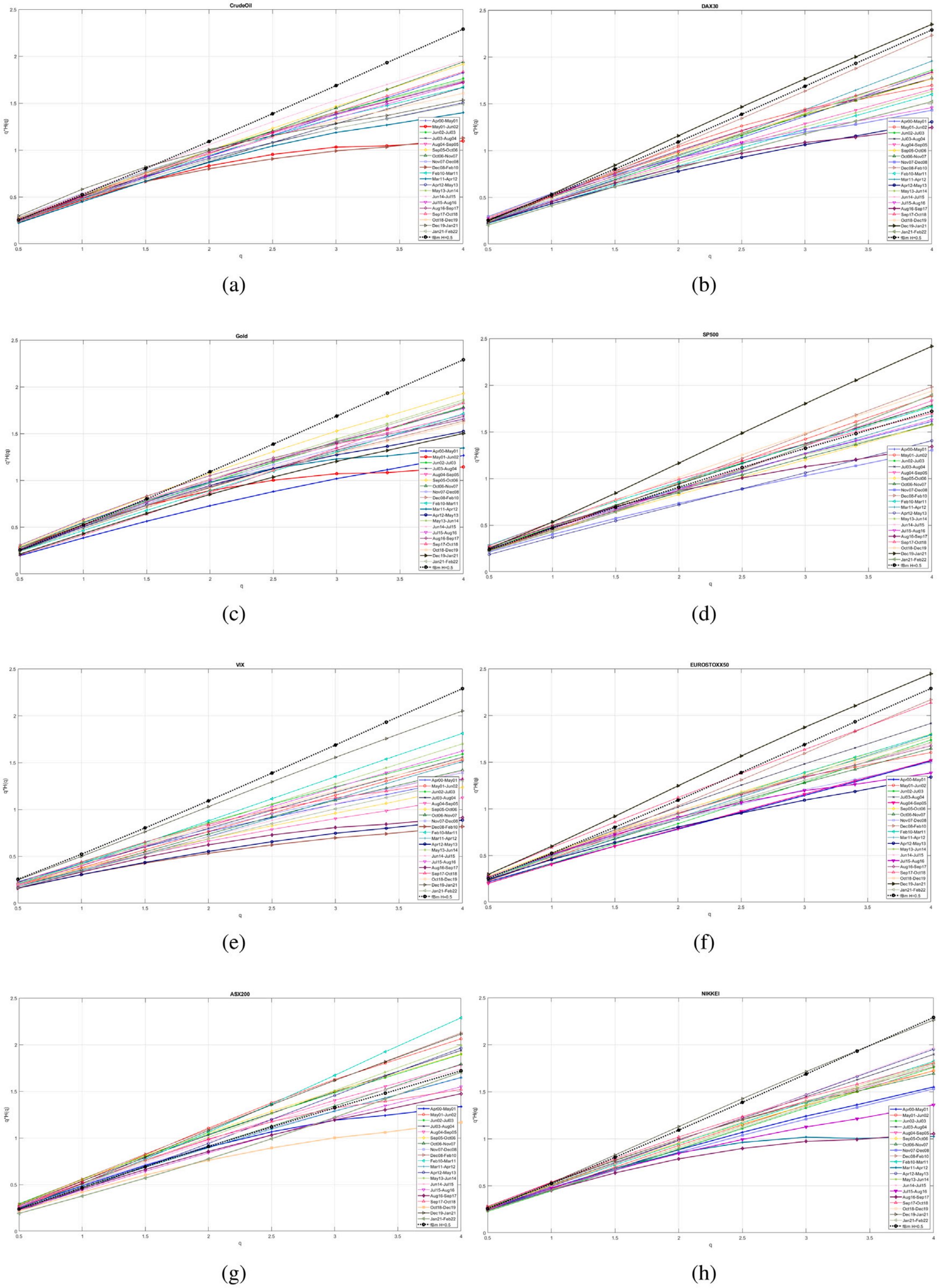


**Fig. 2.** Generalized Hurst exponent for $q = \{0.5, 1, \dots, 4\}$ using non-overlapping windows of 250 observations. Black dotted line corresponds to a simulated fractional Brownian motion with $H = 0.5$.

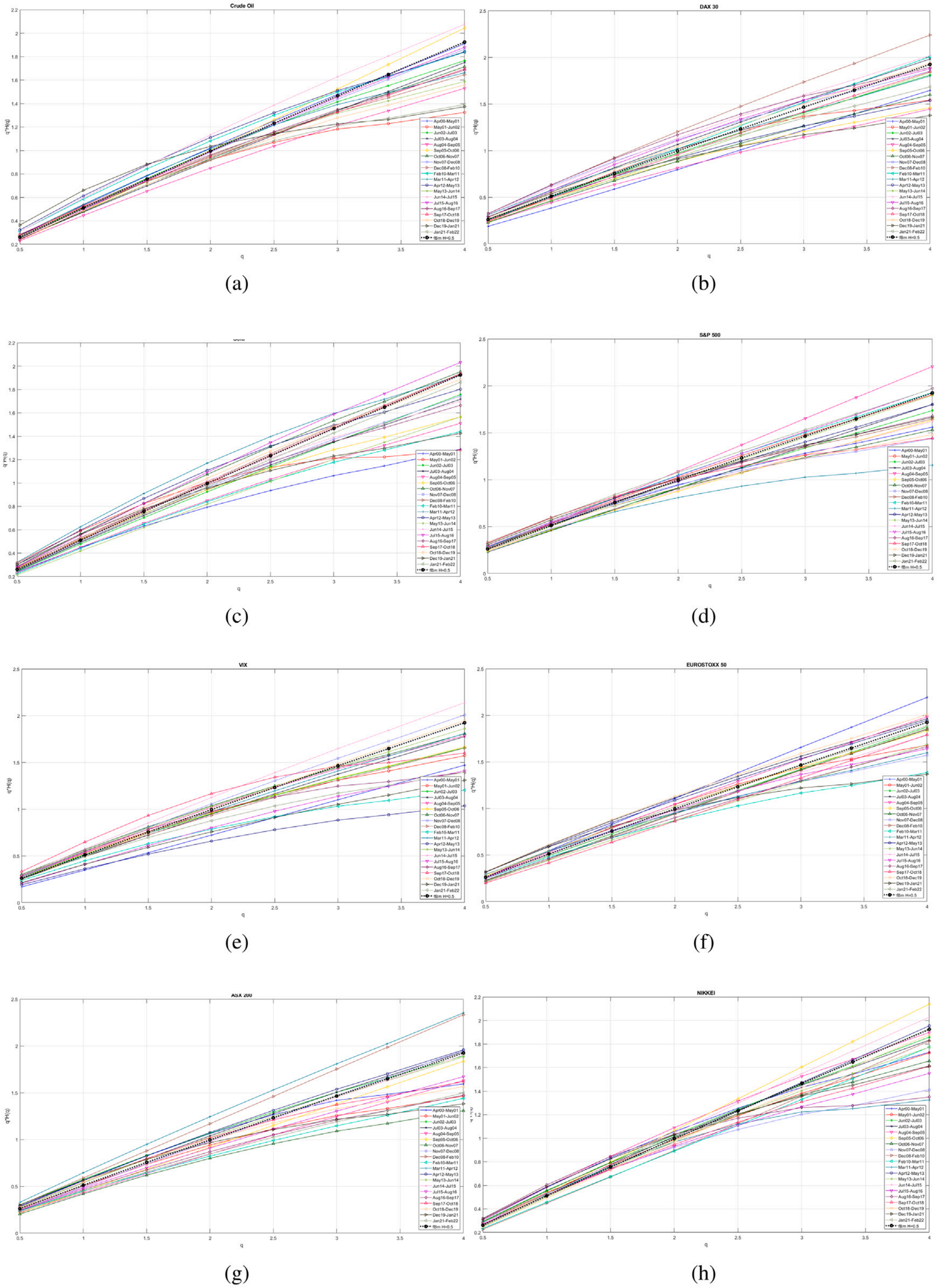


**Fig. 3.** Generalized Hurst exponent for $q = \{0.5, 1, \dots, 4\}$ using non-overlapping windows of 250 shuffled observations. Black dotted line corresponds to a simulated fractional Brownian motion with $H = 0.5$.

**Table 2**
Results of the multifractal spectrum ($\Delta(\alpha) = \alpha_{max} - \alpha_{min}$) of the original time series for each window.

| Period | Gold | Crude oil | VIX | S&P 500 | DAX30 | EuroStoxx50 | ASX200 | NIKKEI |
|---|---|---|---|---|---|---|---|---|
| Apr2000–May2001 | 0.4029 | 0.4802 | 0.2423 | 0.6543 | 0.4328 | 0.4728 | 0.2925 | 0.1982 |
| May2001–Jun2002 | 0.8171 | 0.4233 | 0.4662 | 0.2028 | 0.5472 | 0.4225 | 0.4213 | 0.0759 |
| Jun2002–Jul2003 | 0.2127 | 0.3451 | 0.7823 | 0.4643 | 0.5906 | 0.6039 | 0.2999 | 0.2705 |
| Jul2003–Aug2004 | 0.1992 | 0.2702 | 0.2694 | 0.2104 | 0.3544 | 0.3771 | 0.4401 | 0.4079 |
| Aug2004–Sep2005 | 0.1859 | 0.3605 | 0.4670 | 0.3458 | 0.4461 | 0.2017 | 0.3206 | 0.3756 |
| Sep2005–Oct2006 | 0.3176 | 0.3038 | 0.3471 | 0.3293 | 0.5605 | 0.4331 | 0.5063 | 0.4062 |
| Oct2006–Nov2007 | 0.3225 | 0.5744 | 0.4821 | 0.2738 | 0.3066 | 0.4534 | 0.4890 | 0.3558 |
| Nov2007–Dec2008 | 0.5148 | 0.4023 | 0.2873 | 0.7210 | 0.9272 | 0.8539 | 0.6076 | 1.0420 |
| Dec2008–Feb2010 | 0.2360 | 0.5784 | 0.4530 | 0.2090 | 0.1295 | 0.1662 | 0.0601 | 0.0758 |
| Feb2010–Mar2011 | 0.5827 | 0.1992 | 0.1401 | 0.4767 | 0.5301 | 0.4942 | 0.1391 | 0.3664 |
| Mar2011–Apr2012 | 0.3064 | 0.5267 | 0.0585 | 0.7449 | 0.4131 | 0.5120 | 0.6443 | 0.8414 |
| Apr2012–May2013 | 0.7919 | 0.0641 | 0.2948 | 0.2872 | 0.2669 | 0.3946 | 0.2993 | 0.2624 |
| May2013–Jun2014 | 0.2366 | 0.3440 | 0.4827 | 0.3616 | 0.8411 | 0.5476 | 0.4962 | 0.1393 |
| Jun2014–Jul2015 | 0.4000 | 0.2888 | 0.4225 | 0.5093 | 0.6368 | 0.6637 | 0.2242 | 0.4600 |
| Jul2015–Aug2016 | 0.1723 | 0.5212 | 0.3713 | 0.8053 | 0.2870 | 0.3261 | 0.4568 | 0.6231 |
| Aug2016–Sep2017 | 0.4171 | 0.3528 | 0.5527 | 0.2187 | 0.3290 | 0.3826 | 0.0759 | 0.6550 |
| Sep2017–Oct2018 | 0.0991 | 0.2695 | 0.9096 | 0.9253 | 0.4755 | 0.7654 | 0.6393 | 0.7326 |
| Oct2018–Dec2019 | 0.4747 | 0.3388 | 0.7234 | 0.7179 | 0.2608 | 0.4458 | 0.3288 | 0.4906 |
| Dec2019–Jan2021 | 0.6718 | 0.9855 | 0.1291 | 0.5072 | 0.3005 | 0.4149 | 0.2749 | 0.3445 |
| Jan2021–Feb2022 | 0.1235 | 0.7114 | 0.6037 | 0.4433 | 0.4962 | 0.6364 | 0.4467 | 0.2714 |
| Max | 0.8171 | 0.9855 | 0.9096 | 0.9253 | 0.9272 | 0.8539 | 0.6443 | 1.0420 |
| Min | 0.0991 | 0.0641 | 0.0585 | 0.2028 | 0.1295 | 0.1662 | 0.0601 | 0.0758 |
| Mean | 0.3742 | 0.4170 | 0.4242 | 0.4704 | 0.4566 | 0.4784 | 0.3731 | 0.4197 |
| Std. Dev. | 0.2122 | 0.1995 | 0.2196 | 0.2232 | 0.1963 | 0.1685 | 0.1717 | 0.2528 |

**Table 3**
Results of the average multifractal spectrum ($\Delta(\alpha) = \alpha_{max} - \alpha_{min}$) of 50 independent shuffled realizations of the original time series for each window.

| Period | Gold | Crude oil | VIX | S&P500 | DAX30 | EuroStoxx50 | ASX200 | NIKKEI |
|---|---|---|---|---|---|---|---|---|
| Apr2000–May2001 | 0.3435 | 0.2849 | 0.3177 | 0.3040 | 0.2461 | 0.2463 | 0.3728 | 0.3521 |
| May2001–Jun2002 | 0.4969 | 0.4282 | 0.3475 | 0.2963 | 0.4599 | 0.3936 | 0.4483 | 0.2800 |
| Jun2002–Jul2003 | 0.2688 | 0.2913 | 0.3244 | 0.2756 | 0.2234 | 0.2528 | 0.2635 | 0.2852 |
| Jul2003–Aug2004 | 0.2568 | 0.2637 | 0.3001 | 0.2734 | 0.3140 | 0.2909 | 0.3144 | 0.2913 |
| Aug2004–Sep2005 | 0.3235 | 0.3112 | 0.3293 | 0.2527 | 0.3118 | 0.3013 | 0.2549 | 0.3265 |
| Sep2005–Oct2006 | 0.3223 | 0.2538 | 0.3431 | 0.3259 | 0.2665 | 0.3601 | 0.3039 | 0.3077 |
| Oct2006–Nov2007 | 0.2727 | 0.2591 | 0.3092 | 0.3703 | 0.3241 | 0.2848 | 0.3418 | 0.3319 |
| Nov2007–Dec2008 | 0.3207 | 0.3624 | 0.3266 | 0.4768 | 0.4644 | 0.3934 | 0.2651 | 0.3815 |
| Dec2008–Feb2010 | 0.2963 | 0.4036 | 0.3116 | 0.3315 | 0.2359 | 0.3050 | 0.2974 | 0.2524 |
| Feb2010–Mar2011 | 0.2911 | 0.3672 | 0.3343 | 0.3584 | 0.3372 | 0.3928 | 0.2514 | 0.2501 |
| Mar2011–Apr2012 | 0.5431 | 0.3913 | 0.3055 | 0.3553 | 0.3353 | 0.2903 | 0.3241 | 0.4839 |
| Apr2012–May2013 | 0.5049 | 0.3550 | 0.3437 | 0.3076 | 0.3365 | 0.3013 | 0.3221 | 0.2409 |
| May2013–Jun2014 | 0.2909 | 0.2957 | 0.3092 | 0.2938 | 0.3033 | 0.2842 | 0.3012 | 0.3354 |
| Jun2014–Jul2015 | 0.3433 | 0.3286 | 0.2990 | 0.2580 | 0.2713 | 0.3059 | 0.2778 | 0.3331 |
| Jul2015–Aug2016 | 0.3425 | 0.2812 | 0.3001 | 0.3046 | 0.3835 | 0.4014 | 0.2863 | 0.3619 |
| Aug2016–Sep2017 | 0.3840 | 0.2767 | 0.4123 | 0.3471 | 0.3528 | 0.3199 | 0.3266 | 0.4769 |
| Sep2017–Oct2018 | 0.2768 | 0.2858 | 0.5384 | 0.4705 | 0.3437 | 0.2634 | 0.3467 | 0.3845 |
| Oct2018–Dec2019 | 0.2950 | 0.3380 | 0.3053 | 0.3217 | 0.2722 | 0.3356 | 0.3958 | 0.3165 |
| Dec2019–Jan2021 | 0.3889 | 0.7761 | 0.3583 | 0.3906 | 0.4255 | 0.5631 | 0.5065 | 0.4491 |
| Jan2021–Feb2022 | 0.3045 | 0.3771 | 0.3346 | 0.3257 | 0.3102 | 0.2938 | 0.3715 | 0.2783 |
| Max | 0.5431 | 0.7761 | 0.5384 | 0.4768 | 0.4644 | 0.5631 | 0.5065 | 0.4839 |
| Min | 0.2568 | 0.2538 | 0.2990 | 0.2527 | 0.2234 | 0.2463 | 0.2514 | 0.2409 |
| Mean | 0.3433 | 0.3465 | 0.3375 | 0.3320 | 0.3259 | 0.3290 | 0.3286 | 0.3360 |
| Std. Dev. | 0.0823 | 0.1136 | 0.0543 | 0.0607 | 0.0677 | 0.0730 | 0.0655 | 0.0709 |

## 6. Conclusion

This paper has studied eight time series corresponding to the returns of different financial assets. The sample spans from more than two decades, starting in April 2000 until September 2022. The aim of the study was to assess the changes in long memory and multifractality during several market stressing situations.

The results of this paper uncover several relevant features of financial time series during crises periods, with important implications for investors. Particular focus is given to the 2008 financial crisis and the Covid-19 pandemic.

First, there is a reduction in the informational efficiency during the aforementioned financial and health crises. However, the Covid-19 crisis had harder effects in the long memory behavior than other crises. In particular, it has been found an initial strong antipersistent behavior, followed by a strong persistent behavior.

Two assets deserve specific consideration. On the one hand, Gold, as a safe haven asset, is less affected by crises and behaves more efficiently during all the sample period. On the other hand, VIX time series is mean-reverting in almost all period, except at the beginning of the recovery from the Covid-19 crisis, when persistent behavior emerged. Nevertheless, it immediately returned to the usual mean reverting behavior.

Regarding multifractality, although during most of the sample period the time series show mild symptoms of multifractality, not all crises affect the financial assets in the same way.

One important finding is that Covid-19 pandemic, albeit producing first a decrease and subsequently a rapid persistent increase in the long memory, is not accompanied by an increase in the multifractal behavior.

The results show that the source of multifractality is not only due to autocorrelations, but also to the characteristics of the probability density function of the time series, in particular the presence of fat tails.

Considering that the standard financial models are based on monofractal processes, these results raise some concerns on the limitations of hedging strategies. The time-varying multifractality and long memory requires that investors pay attention to the specific behavior of the time series for their selected investment horizons. Finally, practitioners could consider recalibrating their models during stressed market situations.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request

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