



The impact of COVID-19 pandemic on the dynamic correlations between gold and U.S. equities: evidence from multifractal cross-correlation analysis

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Accepted: 1 April 2022

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Abstract

This study exploits multifractal cross-correlation analysis (MFCCA) to investigate the impact of the COVID-19 pandemic on the cross-correlations between gold and U.S. equity markets using 1-min high-frequency data from January 1, 2019, to December 29, 2020. The MFCCA method shows that the pandemic caused an increase of multifractality in cross-correlations between the two markets. Specifically, the cross-correlations of small fluctuations became more persistent while those of large fluctuations became less persistent, explaining the source of multifractality. The findings of this study carry significant implications for investors, academicians, and policymakers. For example, the increase of multifractality of cross-correlation means that the non-linear relationship between gold and U.S. equity returns prevails more during economic downturns. Therefore, academicians may resort to non-linear techniques to evaluate the relationship between gold and U.S. equity markets during the health pandemic. Moreover, investors can know the value of hedging benefits over different investment time horizons during the pandemic. Finally, policymakers can better assess the economic downturns (i.e., those caused by health pandemics) over the dynamics of cross-correlation between gold and equity markets to make sound financial policies.

Keywords COVID-19 pandemic · Gold · U.S. equity · Multifractality · Cross-correlations · Hedging

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JEL classification G11 · G01 · G15

1 Introduction

Since the first reported case of the COVID-19 virus in Wuhan in December 2019, it infected 275,790,573 people and caused 5,376,566 deaths in 224 countries and territories as of December 21, 2021 (Worldometer Data Tracker 2021). This virus resulted in a health crisis that led to a global economic crisis due to declining sentiment and the implementation of restrictions and lockdowns. Stock markets witnessed the worst turmoil since the 1930s. For example, S&P 500 index price went down from \$3240.09 on December 30, 2019, to \$2237.4 on March 23, 2020, reflecting a decrease of almost 31%. The U.S. unemployment rate increased 3.6% in January 2020 to 14.7% percent in April, the highest level since the Great Depression (Washington post report 2020).¹

The ongoing studies show that stock markets became riskier and more volatile during the COVID-19 pandemic. Zhang et al. (2020) confirm that the pandemic had a solid and increasing impact on the risk levels, as measured by the standard deviation of daily stock market returns, of countries with the highest number of reported COVID-19 cases. The risk levels of all the countries increased dramatically from 0.0071 in February to 0.0196 in March. Albulescu (2020) finds that the spread of coronavirus outside China increases the financial markets volatility index (VIX). Similarly, Ali et al. (2020) decomposed the virus spread into three stages: Phase 1, when coronavirus deaths were limited to China, Phase 2 and 3, which correspond to European Spread and North American Spread, respectively. Their findings indicate that European stock market indices are more volatile during the phase of North American spread. Baker et al., (2020) show that daily stock market swings due to the COVID-19 pandemic are far greater than those witnessed in previous infectious diseases, including the Spanish Flu of 1918–20, which killed around two percent of the world's population. Their explanation hinges on the fact that government policy response to contain the virus spread, such as business closures and travel restrictions, has a lengthier duration than policy response to the Spanish Flu. Onali (2020) also finds that reported cases and deaths of COVID-19 affected the variability of the Dow Jones and S&P500 indices and that their volatility can determine their stock returns. Gormsen and Koijen (2020) used the discounted value of all future dividends models and dividend futures to obtain estimates of growth expectations by maturity. They find that news about U.S. economic relief programs on March 13 improves long-term expectations rather than short-term growth. Yilmazkuday (2021) utilized daily data from December 31, 2019, to May 1, 2020, and the SVAR model to investigate the effect of the COVID-19 pandemic on the S&P 500 Index. His findings reveal that a one percent increase in cumulative daily COVID-19 cases in the U.S. results in about 0.01 and 0.03 percent of a cumulative reduction in the S&P 500 index after one day and one month, respectively. Zaremba et al. (2021) examine the effect of government policy dealing with a pandemic such as a school and workplace closures, public events cancellation, and restrictions on internal and international movements. They find that these strict policies lead to a significant rise in stock market volatility.

Given the documented effects of the COVID-19 pandemic on market risk, it is natural to think about how safe-haven assets such as gold correlate with market return fluctuations

¹ The report can be accessed on this website: <https://www.washingtonpost.com/business/2020/05/08/april-2020-jobs-report/>).

amid the pandemic.² Thus, our study contributes to the open debate of whether gold can be regarded as a safe-haven investment. Many studies indicate that gold can generally perform the safe haven role (Baur and Lucey, 2010; Ciner et al., 2013; Li and Lucey, 2017; Reboredo, 2013; Maghyereh et al. 2018, 2019; Maghyereh and Abdoh, 2021). In contrast, some studies cast doubt on the safe-haven role of gold in certain situations. Lucey and Li (2015) applied the Dynamic Conditional Correlation Multivariate GARCH Model (DCC) to examine precious metals' time-varying safe-haven status, including gold. Their findings indicate that the gold plays the safe-haven role against U.S. equity in certain quarters (Q) of the year [i.e., Q1 1993, Q2 1996, Q4 1997, Q4 2009 (after the financial crises), Q2 2010, and Q4 2010 (following the European sovereign debt crisis)]. Shahzad et al. (2019) show that gold, among other assets, can be considered a weak safe-haven asset if the safe-haven role is studied in the context of the bivariate cross-quantilogram approach.³

More recently, studies used the COVID-19 pandemic as an extreme market bear condition. However, these studies show inconclusive findings regarding precious metals' safe-haven status during the pandemic, including gold. Corbet et al. (2020) analyzed the dynamic correlations between Chinese stock markets and gold, finding that the correlation between Chinese markets (Shanghai and Shenzhen stock exchanges) and gold was negative before the COVID-19 outbreak but grew to a positive during the pandemic. Cheema and Szulczuk (2020) show that gold moves in tandem with stock market indices of the five largest economies in the world from September 17, 2014, to April 16, 2020, thereby concluding that gold did not perform the safe-haven role against stock market losses during the COVID-19 pandemic. In contrast, Ji et al. (2020a, b) study the stability of the tail behavior of mean–variance optimized portfolios between equity indices and safe-haven assets for two periods: pre-crisis from August to December 2019 during-crises period from December 2019–March 2020. Their findings show that most assets became less effective as a safe-haven except gold and soybean commodity futures. Unlike these studies, as mentioned earlier, Akhtaruzzaman et al. (2021) examined gold's safe-haven asset properties for a more extended period during the pandemic using the intraday dataset until April 24, 2020. During the first period phase (December 31, 2019–March 16, 2020), gold is a safe-haven for equity indices such as the S&P 500, confirming the conclusion reached by Ji et al. (2020a, b). However, gold did not keep its safe-haven asset property during the second-period phase (March 17, 2020–April 24, 2020). They justify the findings based on the U.S. monetary and fiscal government intervention to stimulate the economy during the second phase.

Our study uses a more extended period during the pandemic than used by these studies. More importantly, we use multifractal cross-correlation analysis (MFCCA) and the q -dependent detrended cross-correlation coefficient to analyze the change of correlation between the gold return and U.S. equity returns caused by COVID-19. The MFCCA method was developed by Oświęcimka et al. (2014) as an extension of the multifractal

² Baur and Lucey (2010) differentiate between a haven and hedging roles. The former refers to uncorrelation or negative correlation between gold, regarded safe asset, and stocks during crises. The latter refers to uncorrelation or negative correlation during normal market conditions. Since our analysis is conducted during health crises, we use a "safe haven."

³ The reader can refer to Connor et al. (2015) for a literature review about the gold market and its behavioral and economic fundamental aspects.

detrended cross-correlation analysis (MF-DCCA) method of Zhou (2008).⁴ This method can investigate the complex behaviors of autocorrelation and cross-correlation in financial markets, considering the multifractal characteristics of two non-stationary time series. Unlike the other multifractal cross-correlation analysis methods⁵ The MFCCA algorithm enables to compute the arbitrary-order covariance function of two signals as well as the relative signs in the signals (Fan and Li, 2015; Gębarowski et al. 2019; Li et al. 2021; Wątopek et al. 2019; Wang et al., 2021), thereby providing more reliable estimation of multiscale correlations between any two time series (Wątopek et al. 2021). During crises, dynamic correlation analyses like MFCCA may provide additional insights into the safe-haven role of gold against the stock market movements. In the detrended cross-correlation coefficient ρ_q between gold and S&P 500, we find that it is more significant during the pandemic supporting the suitability of MFCCA in our analysis. The method also can avoid the spurious detection of apparent long-range correlation.

Our findings can be summarized in the following four points. First, the cross-correlation between gold and S&P500 is anti-persistent, and the pandemic reduces the degree of anti-persistence. Second, the cross-correlation between gold and S&P500 is negative before the pandemic, and value differs depending on the size of fluctuation (q). However, during the pandemic, the correlations became positive and more independent of q . Third, during the pandemic, the cross-correlation for large fluctuation became lower than for smaller fluctuation, particularly in the long term. Fourth, the cross-correlations between gold and S&P 500 decreased in the long term during the pandemic. The findings resonate with many implications. For example, investors can consider our findings of cross-correlations and multifractality in designing time-varying efficient portfolios during the pandemic. Moreover, forecasting investment risk from gold and equity may be enhanced by considering the long-range cross-correlations and the extent of multifractality. This study focuses on the U.S. market for two main reasons. First, crises in the U.S. market and their volatility and return outcomes can be transmitted to other markets and sectors (see Bekaert et al., 2014; Syriopoulos et al., 2015). Hence, our analysis of the influence of COVID-19 on the correlation between gold and the U.S. market can shed light on the correlation between gold and stock markets in other countries. Second, the pandemic has caused the most extensive spread in reported cases and deaths in the United States, thereby studying the U.S. markets providing an unprecedented correlation between gold and stock market returns.

2 Methodology

This paper utilizes the MFCCA approach to analyze how COVID-19 changes the correlations between gold returns and U.S. equities returns.⁶ This method is proposed by Oświęcimka et al. (2014), which can quantify the multifractal cross-correlations between

⁴ The MF-DCCA method was developed as a combination of the multifractal detrended fluctuation analysis (MF-DFA) method of Kantelhardt et al. (2002) and the detrended cross-correlation analysis (DCCA) method proposed by Podobnik and Stanley (2008).

⁵ Among the most common multifractal cross-correlation analysis methods are the Detrended Fluctuation Analysis (DFA) of Kantelhardt et al., (2001), the Multifractal Detrended Fluctuation Analysis (MFDFA) of Kantelhardt et al. (2002), the Detrended Cross-Correlation Analysis (DCCA) of Podobnik and Stanley (2008), Multifractal Detrended Cross-Correlation Analysis (MFDDCA) of Zhou (2008), and the Multifractal Cross Wavelet Transform (MF-X-WT) analysis of Jiang et al. (2017).

⁶ We thank a reviewer for suggesting the use of the MFCCA approach.

two non-stationary time series. This method also calculates the q -dependent detrended cross-correlation coefficient (ρ_q) proposed by Kwapień et al. (2015). In the following, we briefly introduce this method.

Let us consider that x_k and y_k are two time series of the same length N , where $k = 1, \dots, N$. Then the MFCCA method can be implemented through the following sequence of steps⁷:

Step 1 Determine the corresponding cumulative deviation of the time series as follows

$$X(i) = \sum_{k=1}^i (x_k - \bar{x}), \quad Y(i) = \sum_{k=1}^i (y_k - \bar{y}) \quad i = 1, \dots, N \tag{1}$$

where \bar{x} and \bar{y} are the means of the two-time series, respectively.

Step 2 The cumulative deviation series $X(i)$ and $Y(i)$ have then divided into $N_s \equiv \text{int}(N/s)$ nonoverlapping segments, each with the same length s . Since the length N of the series may not be an integer multiple of sub-interval length s , a short part segment will remain at the end of each series. To get all parts of the series and obtain the $2N_s$ sub-series altogether, the same dividing procedure is repeated starting from the opposite end.

Step 3 Then for each $2N_s$ sub-series, the least-squares method is applied to calculate the local trends $\tilde{X}^v(i)$ and $\tilde{Y}^v(i)$ with a polynomial of k th order fit as $\tilde{X}^v(i) = \alpha_1 i^k + \alpha_3 i^{k-1} + \dots + \alpha_k i + \alpha_{k+1}$ and $\tilde{Y}^v(i) = \beta_1 i^k + \beta_3 i^{k-1} + \dots + \beta_k i + \beta_{k+1}$, where $i = 1, 2, \dots, s; k = 1, 2, \dots; v = 1, 3 \dots, 2N_s$. Then, the detrended covariance $F^v(s, v)$ for each $v = 1, 3 \dots, N_s$ can be determined by

$$F_{xy}^2(s, v) = \frac{1}{s} \sum_{i=1}^s \{ (X_{(v-1)s+i}(i) - \tilde{X}^v(i)) \times (Y_{(v-1)s+i}(i) - \tilde{Y}^v(i)) \} \tag{2}$$

And for each $v = N_s + 1, N_s + 2, \dots, 2N_s$,

$$F_{xy}^2(s, v) = \frac{1}{s} \sum_{i=1}^s \{ (X_{N-(v-N_s)s+i}(i) - \tilde{X}^v(i)) \times (Y_{N-(v-N_s)s+i}(i) - \tilde{Y}^v(i)) \} \tag{3}$$

Here, $F_{xy}^2(s, v)$ takes both the positive and negative values.⁸

Step 4 Obtain the q th-order fluctuation function $F_{xy}^q(s)$ as

$$F_{xy}^q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{N_s} \text{sign}(F^2(s, v)) \left| F^2(s, v) \right|^{\frac{q}{2}} \right\}^{\frac{1}{q}} \quad \text{for } q \neq 0, \tag{4}$$

and

$$F_{xy}^0(s) = \exp \left\{ \frac{1}{2N_s} \sum_{v=1}^{N_s} \text{sign}(F^2(s, v)) \text{Ln} \left| F^2(s, v) \right| \right\} \quad \text{for } q = 0 \tag{5}$$

⁷ Note that most notations and text in this section are taken from Gębarowski et al. (2019), Wątorek et al. (2019), and Li et al. (2021).

⁸ Note that the term $F_{xy}^2(s, v)$ must be a non-negative value in the MF-DFA method.

Step 5 We analyze the scaling behavior of the fluctuation function by observing the log–log plots of $F_{xy}^q(s)$ versus time scale s for each value of q . If $F_{xy}^q(s)$ fluctuates around zero, then there is no fractal cross-correlation between the two-time series. If long-range cross-correlation exists between the two-time series, the power-law relationship is $F_{xy}^q(s) \propto s^{\lambda_{xy}(q)}$, where $\lambda_{xy}(q)$ is the generalized Hurst exponent versus q . If $\lambda_{xy}(q)$ varies with q , then the cross-correlation between the two-time series has multifractal characteristics. In addition, if $\lambda_{xy}(q) < 0.5$ and $\lambda_{xy}(q) > 0.5$, then the two-time series are anti-persistent and persistent, respectively. The exponent $\lambda_{xy}(q) = 0.5$ indicates uncorrelated the two-time series. The range of $\lambda_{xy}(q)$ can measure the degree of multifractality between two series; a higher value of $\Delta H_{xy}(q) = \lambda_{xy}(q_{\text{Minimum}}) - \lambda_{xy}(q_{\text{Maximum}})$ implies a strong level of multifractal behavior.

Finally, based on the detrended covariance's fluctuation function in step 3 above, we can investigate further the cross-correlations shift before and during the COVID-19 period using the q -dependent detrended cross-correlation coefficient $\rho_q(s)$ proposed by Kwapien et al. (2015) as follows;

$$\rho_q(s) = \frac{F_{xy}^q(s)}{\sqrt{F_x^q(s)}\sqrt{F_y^q(s)}}, \quad \rho_q(s) \in [-1, 1] \text{ for } q > 0 \quad (6)$$

where $F_{xy}^q(s)$ denotes the detrended covariance's fluctuation function of two-time series x and y , $F_x^q(s)$ and $F_y^q(s)$ represent the detrended fluctuation function of x and y , respectively. A value of $\rho_q(s)$ close to 1 indicates a higher cross-correlation between two-time series. A zero value of $\rho_q(s)$ shows simply no cross-correlation.

3 Data

The empirical analysis covers the period from January 1, 2019, to December 29, 2020. The dataset consists of the S&P 500 Composite Index and the cash price of an ounce of gold in dollars. We use high-frequency data (intraday data with frequencies of 1 min) to retain a high number of observations and adequately capture the rapidity and intensity of the dynamic interactions among asset prices. For each time series, our sample contains 1,048,575 price quotations. The data were retrieved from Swiss forex bank Dukascopy.⁹ For each data series, we compute the continuously compounded returns as $r(t_m) = Ln\left(\frac{p(t_{m+1})}{p(t_m)}\right)$ where $p(t_m)$ is the price quotation time series at $m = 1, \dots, T$ (Wątorok et al., 2019, 2021; Kwapien et al. 2021).

To study the impact of the COVID-19 pandemic on the dynamic relationship between gold and the U.S. stock market, we divide each time series into two sub-periods. The first corresponds to the period before the emergence of COVID-19 (January 1, 2019–December 31, 2019), and the second period corresponds to the emergence of COVID-19 (January 1, 2020–December 29, 2020).¹⁰ The price time series of the S&P 500 Composite Index and the cash price of gold for the two periods are shown in Fig. 1. It is clearly shown

⁹ Available at <https://www.dukascopy.com/swiss/english/marketwatch/historical/>.

¹⁰ The outbreak of the COVID-19 pandemic was first identified in Wuhan, China, on December 31, 2019.

that the S&P index has a higher price than gold before the pandemic, but its level has decreased during the pandemic reaching the exact value of gold price. Since March 2020, the gold and equity values have increased steadily but slowly. We also present the logarithmic returns in Fig. 2. The figure shows that the volatility of S&P equity returns is remarkably higher during the pandemic than before, especially from February 2020 to May 2020. The volatility of gold also increased during the pandemic but with less degree than the U.S. equity.

4 Empirical results

4.1 Cross-correlation coefficient $\rho_q(s)$

We test whether there is a cross-correlation between gold and the S&P equity index before and during the pandemic. Figure 3 labels the q -dependent detrended cross-correlation coefficient $\rho_q(s)$ over different time scales (s). For $q > 0$, the $\rho_q(s)$ likes the standard correlation coefficient, which ranges between -1 and 1. However, unlike the standard one, it reflects the actual correlation between gold and the S&P500 index even with stationarity levels. A value of $\rho_q(s)$ close to 1 indicates a higher cross-correlation between two-time series, and a zero value of $\rho_q(s)$ shows no cross-correlation. Figure 3 shows several two exciting findings. First, the cross-correlation between gold and S&P500 is negative before the pandemic, and value differs depending on the size of fluctuation (q). However, during the pandemic, the correlations became positive and more independent of q . Second, during the pandemic, the cross-correlation for large fluctuation became lower than for smaller fluctuation, particularly in the long term.

4.2 Multifractal cross-correlation analysis (MFCCA)

To investigate the multifractal cross-correlations between gold and S&P 500, Fig. 4 shows the log-log plots of the fluctuations function $F_{xy}^q(s)$ versus time scale s for each value of q . In general, the log-log relation curves (or slopes) are linear for most values of q , indicating a power-law cross-correlation between gold and S&P 500 time series. Since $F_{xy}^q(s)$ increases with s , the time scaling behavior exists, and thus we can conclude that the two-time series are cross-correlated in the long range. When the two-time series are the same, then MF-DCCA becomes MF-DFA, as shown in the last two plots of the figure. The slightly decreasing slope with the increase of q implies that all the time series display a multifractal behavior. During the pandemic, the slopes became lower, indicating that the cross-correlations between gold and S&P 500 decreased in the long term.

Figure 5 contains information on how the multifractal cross-correlation scaling exponent $\lambda_{xy}(q)$ (in blue color) and the mean generalized Hurst exponent $h_{xy}(q)$ (in red color), change with the increase in q . If $h_{xy}(q = 2)$ is greater than 0.5, it then indicates that the cross-correlations of the time series pair are positive persistent. If $h_{xy}(q = 2) < 0.5$, the cross-correlations of the time series pair are negative persistent, meaning that the time series fluctuations move in the opposite direction. There are no correlations if $h_{xy}(q = 2) = 0.5$.

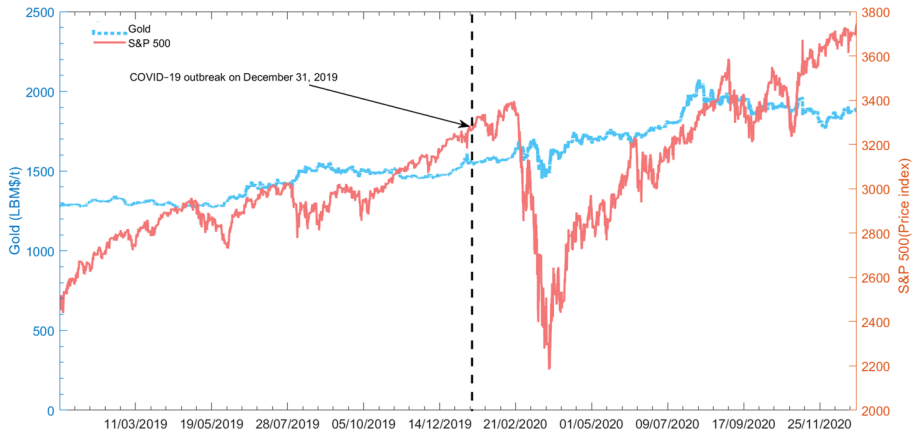


Fig. 1 Time evolutions for the price series from January 1, 2019 to December 29, 2020

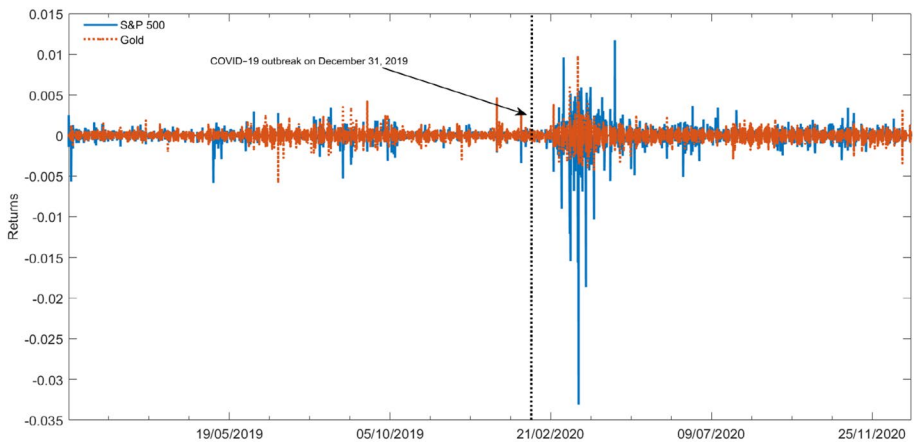
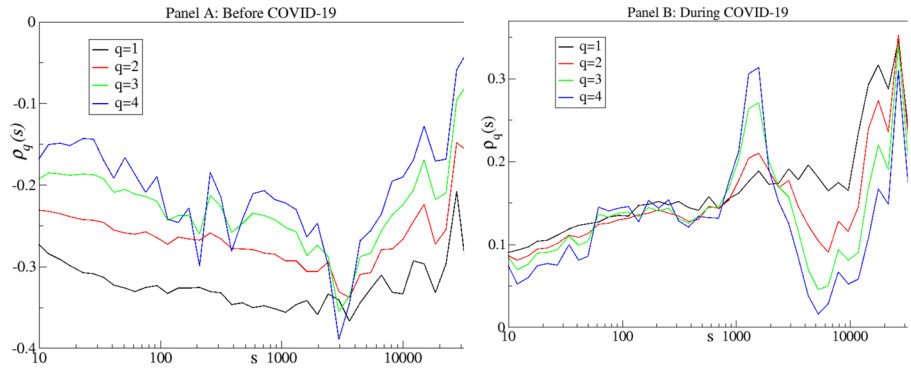


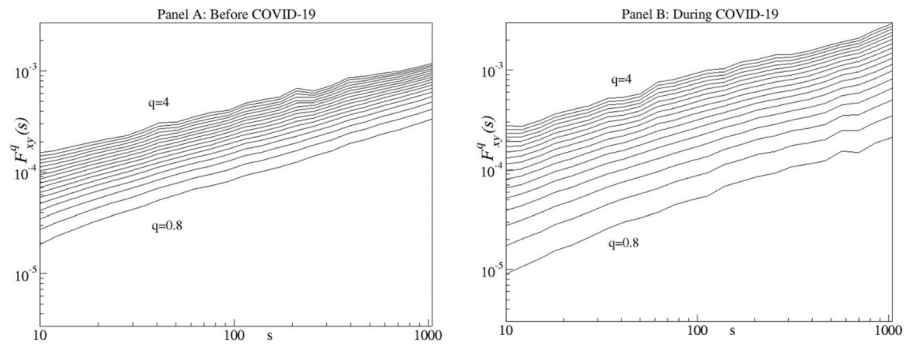
Fig. 2 The returns series from January 1, 2019, to December 29, 2020

Note first that the Hurst exponent, when $q = 2$ is close to 0.5, indicates that the auto-correlation of gold and S&P 500 series is almost zero. This cross-correlation became negative during the pandemic as the Hurst exponent value declined below 0.5. In addition, the fluctuation of gold and S&P500 returns during the pandemic shows a higher multifractality than their fluctuation before the pandemic. The extent of multifractality of cross-correlations can be derived by calculating the range of $h_{xy}(q)$, where a larger $\Delta H_{xy} = h_{xy}(q_{\text{Minimum}}) - h_{xy}(q_{\text{Maximum}})$ reflects a high level of multifractal nature. The range of h (recall that higher h reflects a higher long-range cross-sectional correlation) during the pandemic ($0.53 - 0.45 = 0.08$) is slightly lower than before the pandemic ($0.54 - 0.43 = 0.11$).



Notes: The plot represents the detrended cross-correlation coefficient, ρ_q , for different time scales (s), for $q = 1, 2, 3,$ and 4 . The value of $\rho(s)$ ranges from -1 to 1 . A closer value to 1 means the series pair has a higher cross-correlation. When $\rho(s) = 0$, there exists no cross-correlation.

Fig. 3 Cross-correlation coefficient (ρ_q) for two periods



Notes: The figure represents the Log-log plots of cross-correlation fluctuation function $F_{xy}^q(s)$ versus time scale s for each value of q from 0.8 to 4 with step 0.2 .

Fig. 4 Log–log plots of fluctuation function ($F_{xy}^q(s)$) for two periods

4.2.1 Additional tests

We investigate whether gold is a safe haven for U.S. equities during the COVID-19 pandemic by computing the optimal hedge ratios. In our case, gold is considered a cheap hedge for U.S. equities if the associated hedge ratio is close to zero. Following Baur and McDermott (2010), the gold is characterized as a strong (weak) hedge if it is negatively correlated (uncorrelated) with U.S. equities. Strong (weak) safe haven status can be given to gold when negative (low) correlations are observed during the COVID-19 pandemic.

We utilize multivariate generalized autoregressive conditional heteroskedasticity (DCC-GARCH).¹¹ Figure 6 displays the conditional volatility of gold and U.S. equities returns.

¹¹ The DCC-GARCH was first proposed by Engle (2002). The model is estimated in two steps. In the first step, we compute a time-varying conditional variance using a multivariate GARCH (1, 1) process with Student’s t-copulas. The time-varying correlation matrix is calculated using the standardized residuals from the first step GARCH model in the second step.

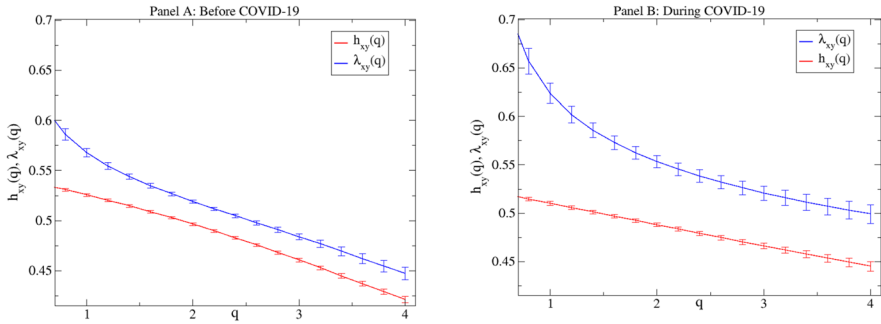


Fig. 5 Multifractal cross-correlation generalized Hurst exponents. (Color figure online)

The gold and S&P500 index volatility peaked during the pandemic, particularly during March 2020. However, the volatilities declined and reached a similar level before the pandemic in May. The reason behind the unprecedented increase in the volatility of the S&P 500 and gold in March may be due to the U.S. national emergency over coronavirus on March 13 2020.

Next, we turn to the dynamic conditional correlations between gold and U.S. equities over the entire sample period, as shown in Fig. 7. The plot of correlations shows considerable volatility overtime during the sample period indicating that the connectedness between gold and U.S. equity is time-varying. The conditional correlation is negative before the pandemic. During the early period of the pandemic, the correlation reached the lowest level over the whole sample period on February 21, 2020. After that day, the correlation increases to a positive level during March and April but starts to decline during May, reaching back to the negative levels. Overall, the findings indicate that gold acts as a strong, safe-haven during the early period of the pandemic but not during the U.S. national emergency period.

To investigate whether different optimal diversification strategies exist before and during the COVID-19 period. We construct the optimal hedge ratios in two-asset portfolios utilizing the estimated conditional volatility from the DCC-GARCH. Optimal hedge ratios are the proportion of the risk of asset i that can be hedged by taking a short position in the hedging instrument j that minimizes the variance of the portfolio containing both assets. In the context of our study, a high hedge ratio, associated with high correlation, indicates that an investor who holds an equity portfolio can hedge a large proportion of his long position by shorting gold while maintaining risk at the lowest possible levels. On the contrary, a low hedge ratio, associated with low correlation, indicates that hedging would not be effective, though there would still be diversification benefits. Following Kroner and Sultan (1993), the hedge ratio ($\beta_{ij,t}$) can be computed as:

$$\beta_{ij,t} = \frac{Cov(r_{it}, r_{jt})}{var(r_{jt})} = \frac{h_{ij,t}}{h_{jj,t}} \tag{7}$$

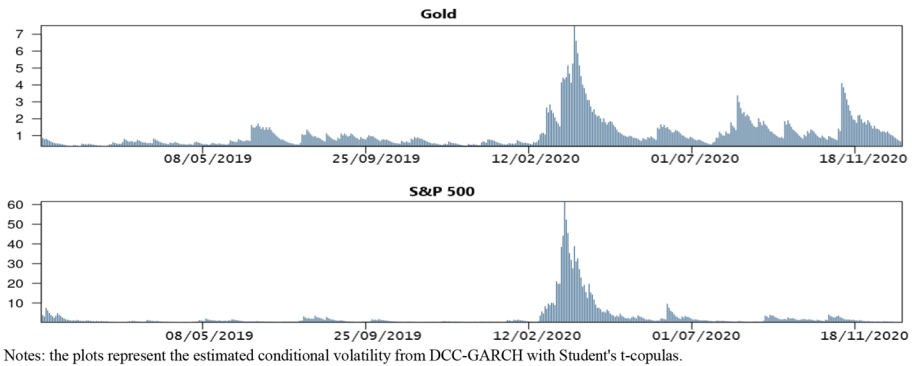


Fig. 6 Conditional volatility

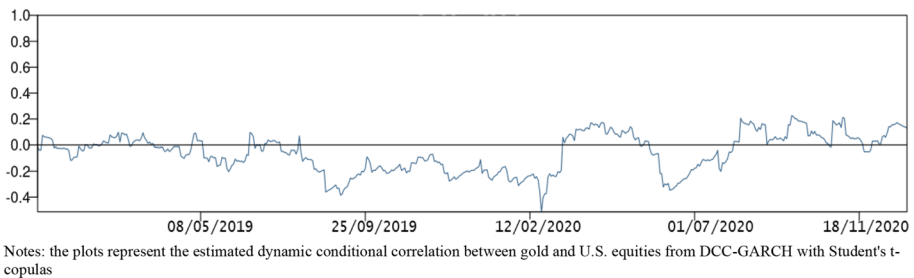


Fig. 7 Dynamic conditional correlation

where $h_{ij,t}$ is the time-varying conditional covariance between gold and U.S. stock market, and $h_{ji,t}$ is the time-varying conditional variance of the U.S. stock market at time t (see, Maghyereh et al. 2017).¹²

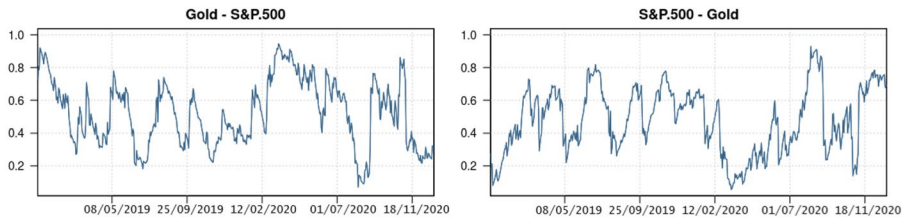
The evolutions of the hedge ratios are presented in Fig. 8. The left side figure “Gold-S&P 500” shows the value of the hedge ratio between a long position in gold and a short position in the S&P 500. A high value indicates a cheaper hedge for a \$1 long position in gold. The figure shows it is cheaper to hedge the risk from investing in gold by shortening the position in S&P 500, particularly during February 2020. In contrast, the right-side figure “S&P 500-Gold” shows that it is more expensive to hedge the long S&P 500 by using gold, particularly during March 2020. It should be noted that these hedge ratios do not convey hedging effectiveness.

Finally, we analyze the hedge effectiveness of the U.S. stock-gold portfolio during the COVID-19 using the hedging effectiveness index (Batten et al. 2021) which is given as:

$$HE = \beta_{ij,t}^2 \frac{h_{it}}{h_{jt}} \tag{8}$$

where h_{it} and h_{jt} are the conditional variances of gold and U.S. stock returns, respectively, a higher HE value indicates that the hedge reduces variance (risk).

¹² We construct dynamic hedge ratios using a rolling window analysis with out-of-sample forecasts.



Notes: the plots represent the estimated dynamic hedge ratio computed from the DCC-GARCH with Student's *t*-copulas.

Fig. 8 Dynamic hedge ratios (long/short)

Table 1 Hedge effectiveness

	Full sample	Before COVID-19	During COVID-19
S&P 500/Gold	0.32** (0.01)	0.57*** (0.00)	0.24 ** (0.03)
Gold/S&P 500	0.76*** (0.00)	0.72*** (0.00)	0.77*** (0.00)

Numbers in brackets are the associated *p*-values. ** and *** indicate the levels of significance at 5% and 1%, respectively

The results for the hedging effectiveness over the entire sample and at subsamples before and during the COVID-19 are shown in Table 1. The hedging effectiveness of gold before the pandemic was positively significant with a value equal to 0.57, indicating that the proportion of the S&P 500 variance eliminated from making a short position in gold is 57%. However, gold loses its hedging effectiveness significantly during the pandemic, indicating that investing in gold may not reduce the variance of U.S. equity return. On the other hand, S&P 500 hedging effectiveness is positive and significant even during the pandemic, indicating that making a short position in S&P 500 index can reduce the variance of gold.

5 Conclusion

In this study, we examine the impact of the COVID-19 health pandemic on the cross-correlation and its multifractality between gold and U.S. equity (as represented by the S&P 500 index). We divide each time series into two sub-periods. The first corresponds to the period before the emergence of COVID-19 (January 1, 2019–December 31, 2019), and the second period corresponds to the emergence of COVID-19 (January 1, 2020–June 1, 2020).

We use multifractal cross-correlation analysis (MFCCA) and the *q*-dependent detrended cross-correlation coefficient to analyze the change of correlations between the gold return and U.S. equity. We document the following findings. First, the cross-correlation between gold and S&P500 is anti-persistent, and the pandemic reduces the degree of anti-persistence. The cross-correlation between gold and S&P500 is negative before the pandemic, and value differs depending on the size of fluctuation (*q*). However, during the pandemic, the correlations became positive and more independent of *q*. Third, during the pandemic, the cross-correlation for large fluctuation became lower than for smaller fluctuation, particularly in the long term. Fourth, the cross-correlations between gold and S&P 500 decreased in the long term during the pandemic.

The findings have important implications for investment decisions and return forecasting. Given our findings that the correlation between S&P 500 and gold is higher during the pandemic, it would be cheaper to perform a hedging strategy by taking a long position in one asset and a short position in the other asset during the pandemic. The increase in the multifractality of cross-correlation between gold and S&P 500 during the pandemic suggests that the non-linear relationship between gold and U.S. equity returns prevails more during economic downturns. Therefore, academicians may resort to non-linear techniques to evaluate the relationship between gold and U.S. equity markets during the health pandemic.

Funding Funding was provided by United Arab Emirates University, 31B135-UPAR -3- 2020, AkthamMaghyereh.

Declarations

Conflict of interest The authors have not disclosed any competing interests.

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