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Bitcoin’s price efficiency and safe haven properties during the COVID-19 pandemic: A comparison

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ABSTRACT

As the COVID-19 outbreak became a global pandemic, traditional financial market indicators were significantly affected. We examine the price efficiency and net cross-correlations among Bitcoin, gold, a US dollar index, and the Morgan Stanley Capital International World Index (MSCI World) during the four months after the World Health Organization officially designated COVID-19 as a global pandemic. Using intraday data, we find that Bitcoin prices were more efficient than the US dollar and MSCI World indices. Using a detrended partial-cross-correlation analysis, our results show that net cross-correlations vary across time scales. Our results suggest that when the time scale is greater than two months, gold can be considered as a safe haven for investors holding the MSCI World and US dollar indices and when the time scale exceeds three months, Bitcoin can be considered a safe haven for the MSCI World index.

1. Introduction

Financial markets experience periodic crises because of systemic failures, such as the global financial crisis of 2008, and exogenous shocks such as the COVID-19 pandemic. These recurring crises have serious consequences for economic growth and employment and increase the risk for financial institutions (Horta et al., 2014). They also have implications for financial returns globally because asset prices behave differently during, before, and after financial crises (Cajueiro et al., 2009; Kumar, and Deo, 2013). The unprecedented magnitude of the COVID-19 crisis brought economic activity to a near standstill in many countries, caused enormous social disruption, and inflicted both physical and psychological damage to millions of people (Schell et al., 2020). Given the economic uncertainties related to the trajectory of the pandemic, it is understandable that market reactions have been erratic. Investors have been deluged by a constant flow of information through social media, press and television, and official announcements. This information flow can be confusing, conflicting, and sometimes misleading, exerting a significant influence on the dynamics of the stock markets (Cepoi, 2020) and causing volatility in security prices.

During periods of extreme uncertainty, investors search for “safe havens” to reduce risk, limit losses, and protect the value of their portfolios. Prior research has established distinctions between terms such as “hedge,” “diversifier,” and “safe haven” although these terms are often used interchangeably in the popular financial press. A diversifier is an asset that is positively but not perfectly

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Fig. 1. Prices and returns of Bitcoin, gold, a US dollar index, and the MSCI World index over five minute intervals for the period from March 11, 2020, to July 10, 2020.
correlated with another asset or portfolio, while a hedge is an asset that is uncorrelated or negatively correlated with another asset or portfolio (Baur and Lucey, 2010). A safe haven differs from a hedge in that it is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil (O’Connor et al., 2015). The main objective of a safe haven asset is to help investors mitigate downside market risk during periods of market turmoil (Ji et al., 2020). Baur and McDermott (2010, p.1889) distinguish between strong and weak safe havens stating that “a strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, e.g., in times of falling stock markets.” An important aspect of this distinction is the length of the effect. While a hedge holds generally, the key property of a safe haven is that it is required to hold only in certain periods, e.g., in a financial crisis. While investors need to hedge or diversify their portfolios during all times, safe haven assets retain or increase their value during periods of market crises.

The most extensively researched safe haven in the literature is gold, with several empirical studies finding gold to be both a safe haven and hedge. For example, Baur and McDermott (2010) found that gold was a strong safe haven for several developed markets during the 2008 financial crisis. Bredin et al. (2015) found that gold served as a safe haven during various financial crises but not during the 1980 economic contraction. Reboredo (2013) reported evidence for gold as a safe haven, hedge, and diversifier with respect to movements in the US dollar exchange rate, and Conlon et al. (2018) demonstrated gold’s ability to serve as a hedge against inflation. Choudhry et al. (2015) showed that while gold has been a safe haven in pre-crisis periods, they found no evidence that it served that purpose during the subprime mortgage crisis. He et al. (2018) concluded that gold is usually a hedge and, at worst, acts as an excellent diversifier of portfolio risk.

The liberalization and globalization of financial markets in recent years has provided investors with more choices of assets than previously available. The development and subsequent growth in the popularity of digital currencies have made an entirely new asset class available that could be a safe haven during periods of crisis alongside traditional assets such as gold. The COVID-19 pandemic is the most severe health emergency the World Health Organization (WHO) has faced (BBC News website, 2021). As per WHO website (WHO Coronavirus (COVID-19) Dashboard, 2021) as of June 1, 2021, over 170,426,245 million people have been infected, and over 3,548,628 million people have died, making COVID-19 a public health crisis of unprecedented proportions. The economic disruptions and dislocations caused by the pandemic have affected financial markets globally, creating extreme volatility in asset prices. In this study, we examine whether Bitcoin could be considered a safe haven during this period of market turmoil. We do so by examining the price efficiency and net cross-correlations among Bitcoin, gold, the US dollar, and the Morgan Stanley Capital International World Index (MSCI World), which tracks the returns of 23 equity markets in developed countries around the world.

According to the efficient market hypothesis, price efficiency (in its weak form) exists when market participants cannot realize abnormal future returns on the basis of past information because current market prices fully reflect publicly available information (Fama, 1970). The actual behavior of markets can deviate from this assumption because of collective errors in investors’ judgment, especially during periods of high uncertainty. Consequently, price irregularities and even predictable patterns in market returns appear from time to time and may even persist for short periods. In addition to the negative consequences for the allocation of resources in an economy, an inefficient market has great arbitrary power, increasing information asymmetry and market risk (Malkiel, 2003). If markets were perfectly efficient, there would be no incentive for professionals to invest time and resources into discovering information that is not yet reflected in market prices (Grossman and Stiglitz, 1980). Furthermore, the efficiency of a market or asset varies over time (Kim et al., 2011); therefore, an asset’s pricing efficiency should be monitored over time. Especially in times of financial crisis, such monitoring should be done before, during, and after the crisis as assets are more susceptible to changing behavior in such periods. Prior research suggests that during financial crises, assets become more volatile and less efficient and regain efficiency over time (Kim et al., 2011). Given the relatively short history of Bitcoin and the severity of the COVID-19 pandemic that has caused substantial turbulence in financial markets, it is important to investigate the safe haven properties of Bitcoin during this period of extreme volatility.

2. **Bitcoin as a safe haven during the COVID-19 crisis**

Since its introduction in 2008, Bitcoin has been the subject of considerable controversy and debate both in academia and in the public arena. Bitcoins are exchanged over a peer-to-peer electronic cash system and have “no association with any higher authority, [has] no physical representation and are infinitely divisible” (Corbet et al., 2019). Bitcoin’s supply is based mostly on the security of an algorithm and its value is ultimately based on market demand. It is backed neither by any tangible asset nor by a government. While the debate continues as to whether Bitcoin is a currency, a commodity, an investment, or a collectible, its popularity and value have increased dramatically since its early days. Priced at about $0.08 when it began trading in July 2010, Bitcoin’s price was close to $20,000 in 2017 and has fluctuated wildly since then, climbing above $60,000 in early 2021 followed by wild gyrations. It has also led to the creation of other cryptocurrencies, such as Ethereum and Ripple. The fact that the vast majority of Bitcoins are held in dormant accounts (Weber, 2014) suggests that it is being used more as a speculative asset than as a functioning currency.

Bitcoin experienced considerable volatility in the months after the WHO declared COVID-19 a global pandemic. The WHO’s announcement was made on March 11th, 2020, and Bitcoin’s price declined more than 40% between March 6th and March 13th (from $8,900 to $5,165), reaching its lowest level in a year. This decline was not confined to Bitcoin; other financial assets also experienced a comparable loss in value as shown in Fig. 1. However, compared to other assets, Bitcoin’s price recovery was much faster. Between April 25, 2020, and July 10, 2020, the price of Bitcoin rose from USD 7,542 to USD 9,243, a level well above its price during the months before the outbreak. By March 2021 it was fluctuating between USD 50,000 and USD 60,000.

The economic uncertainty caused by the pandemic has led many researchers to examine whether Bitcoin could serve as a store of value, a source of portfolio diversification, or a safe haven during this period of crisis, with the results varying considerably across
studies. Corbet et al. (2019) provided a comprehensive review of the growing body of research on cryptocurrencies noting that while some studies found that cryptocurrencies can serve as a safe haven, others found the exact opposite. For example, Goodell and Goutte (2021a) found that the price of Bitcoin rose in the days following the outbreak. Corbet et al. (2020b) found that cryptocurrencies acted as a store of value during the crisis period and as a safe haven, similar to precious metals. Before the COVID-19 pandemic, Urquhart and Zhang (2019) had found that Bitcoin acted as a safe haven, a hedge, and a diversifier versus a range of international currencies. Similar results have been reported by Wang et al. (2020); Aysan et al. (2019); Mensi et al. (2020), and Kilber et al. (2019). Shahzad et al. (2019) found weak support for Bitcoin as a safe haven, as revealed by the fact that its behavior as a safe haven was time-varying. Ji et al. (2020) analyzed the period in which the pandemic affected the financial market most severely (between December 2019 and March 2020) and found that Bitcoin role as a safe haven degenerated during this period. Goodell and Goutte (2021b) found that Bitcoin is not a safe haven for stocks. Corbet et al. (2020a, 2020b) and Conlon and McGee (2020) suggested that during periods of market crises, Bitcoin is neither a safe haven nor a hedge but an amplifier of contagion. Smales (2019) argued that Bitcoin cannot be considered a safe haven because it is more volatile, less liquid, and costlier to transact than other assets. These differing results may be attributable to differences in sample composition, inference procedures, and the asset classes against which cryptocurrencies were compared. For example, compared to studies reporting that Bitcoins have the potential to act as a safe haven, studies that found negative results for Bitcoin’s hedging and safe haven properties typically cover fairly long time periods, sometimes starting years before the COVID-19 outbreak. We provide a summary of the results of empirical studies examining the role of Bitcoin as a safe haven in Table 1a and 1b.

This study focuses on Bitcoin’s usefulness as a safe haven. Given that the COVID-19 pandemic is the first major global economic crisis since Bitcoin was introduced, this gives us an opportunity to investigate whether Bitcoin behaves as a safe haven compared to other types of assets. We examine Bitcoin’s price efficiency along with those of gold, the US dollar index, and the MSCI (World Stock Index) using intraday data and the net cross-correlations among them during the first four months of the pandemic.

3. Methods

3.1. Data

We compared Bitcoin to three other assets, namely, gold, the US dollar, and the MSCI World Index representing a precious metal commodity, a currency, and the global developed country stock markets, respectively. Following Cepoi (2020), the starting point for our data collection was March 11, 2020, the day the WHO declared COVID-19 a global pandemic. The final date of the analysis was

| Study | Sample | Method | Findings |
|-------|--------|--------|----------|
| Goodell and Goutte (2021b) | Cryptocurrencies (Bitcoin, Ethereum, Litecoin and Tether) and Equity indices (FTSE 100, EUROSTOXX, S&P 500, SWISS Index, IBEX 35, DAX, CAC 40, and CBOE VIX) between February 26th, 2019 and February 9th, 2021. | Correlation analysis, wavelet coherence analysis, and neural network analysis. | Co-movements between cryptocurrencies and equity indices gradually increased as COVID-19 progressed. However, most of these co-movements are either modestly positively correlated, or minimal, suggesting cryptocurrencies in general do not provide a diversification benefit during either normal times or downturns. |
| Corbet et al. (2020a, 2020b) | Shanghai and Shenzhen Stock Exchange indexes, Dow Jones Industrial Average, West Texas Intermediate crude oil, gold and Bitcoin. Daily and hourly data between March 11, 2019, to March 10, 2020. | GARCH (1,1) | In times of serious financial and economic disruption, cryptocurrencies do not act as hedges or safe havens but rather as amplifiers of contagion. |
| Conlon and McGee (2020) | Bitcoin and S&P 500 index daily data over three periods: July, 2010 to March, 2020; April, 2016; March 21, 2019 to March 20, 2020. | MCVaR (four-moment modified VaR) | Results cast doubt on Bitcoin’s ability to shelter investors from market turbulence. |
| Ali et al. (2020) | Daily prices and returns of MSCI indices for the nine countries most affected by COVID-19 (China, the US, the U.K., Italy, Spain, France, Germany, Switzerland, and South Korea, along with the MSCI World, Europe and Asia indices, the S&P 500, the US Treasury bonds core index (ICE core), Bitcoin, crude oil (WTI spot) and gold) between January 1, 2020 and March 20, 2020, dividing the sample into two periods, Epidemic (December 2019 to March 10, 2020) and Pandemic (post-March 30, 2020), as well as different phases of the pandemic. | EGGARCH | All assets were impacted by COVID-19. Early epicenter China stabilized while the global markets went into a free-fall, especially in the later phase of the spread. Even relatively safer commodities suffered as the pandemic moved into the US. |
| Chen et al. (2020) | Hourly data on Bitcoin prices and volume in US dollars (BTC/USD), and the Cboe Volatility Index (VIX), between January 15, 2020 and April 24, 2020. | Vector Autoregressive Models (VAR) | Negative Bitcoin returns and high trading volume can be explained by fear sentiment regarding COVID-19. Bitcoin was not a safe haven during the pandemic. |
| Dutta et al. (2020) | Crude oil, gold, and Bitcoin for the period from December 2014 to March 2020. | DCC-GARCH model | Gold is a safe haven asset for global crude oil markets, while Bitcoin acts only as a diversifier for crude oil. |

4
The degree of multifractality is expressed as exponent is equal to 0.5, the time series has an independent or short-range dependent structure (random walk behavior) (Ihlen, 2012). A Hurst exponent between 0.5 and 1.0 means that a time series has a long-range dependence (i.e., it is correlated). In the special case when the Hurst exponent, which ranges from 0 to 1.0. A Hurst exponent between 0 and 0.5 means that a time series has an anti-correlated structure and dynamics (Dutta et al., 2013). In recent years, several methodological approaches have been developed for the specific purpose of studying multifractality in time series data. The best known of these approaches is MF-DFA (Salat et al., 2017), in particular the detailed six-step process proposed by Kantelhardt et al. (2002). The measurement of multifractality in MF-DFA is based on the Hurst exponent; the smaller the Δh coefficient, closer to 0.5; therefore, small values of Δh indicate efficiency in the time series.

Table 1b
Positive view of cryptocurrency behavior during the COVID-19 crisis.

| Study               | Sample                                                                 | Method                                   | Findings                                                                 |
|---------------------|------------------------------------------------------------------------|------------------------------------------|--------------------------------------------------------------------------|
| Ji et al. (2020)    | Daily closing/spot price of Bitcoin, gold, forex rates (EUR-USD and CNY-USD), crude oil (WTI), and soybean commodity futures between March 11, 2019, and March 10, 2020 | VAR, GARCH (1,1) and cross-quantilogram approach | Bitcoin, CNY-USD, and crude oil futures act as safe havens for equity indices during normal times but did not do so during the COVID-19 period. Gold and soybean futures have strong safe haven roles. The safe haven property was found to be changing over time and sensitive to the choice of markets. |
| Conlon et al. (2020)| Cryptocurrencies (Bitcoin, Ethereum, and Tether); equity indices (MSCI World, S&P 500, FTSE 100, FTSE, MIB, IBEX, and CSI 300) between April 2010 and April 2020 | Two-moment value at risk (MCVaR)         | Tether was the only cryptocurrency that was safe haven during the pandemic. |
| Le et al. (2021)    | Twenty-three spot exchange rates versus the US dollar and a US dollar index, 11 commodities (two precious metals, five agriculture, and four energy), 14 international equity indices, UST bonds (30 year maturity), and Bitcoin between January 1, 2019, and April 30, 2020. | Cross-spectral analysis and tail-depending networks | Bitcoin and US Treasury bonds are both disconnected from tail-depency networks, suggesting their safe haven characteristics. |
| Iqbal et al. (2021) | Daily returns of the top 10 cryptocurrencies (BTC, ETH, XRP, BCH, BSV, LTC, BNB, EOS, ADA, and CRO) for the period from January 1, 2020, to June 15, 2020. | Quantile-on-Quantile Regression       | The changing intensity levels of COVID-19 affect bearish and bullish market scenarios for cryptocurrencies differently (asymmetric impact). During times of stress, panic, and uncertainty, Bitcoin and CRO performed better compared to other cryptocurrencies. |
| Le et al. (2020)    | Daily closing/spot price of bitcoin (CoinDesk price index), gold (source of gold-LBMA), forex rates (EUR-USD and CNY-USD), the WTI crude oil (rolling front-month futures contract), and soybeans commodity futures. between November 2018 and June 2020 | Vector Autoregression (VAR)       | Traditional assets, gold and oil as well as Bitcoin and green bonds are useful hedges compared to other assets. |
| Mariana et al. (2021)| Bitcoin, Ethereum, S&P500, and gold spot price daily returns between July 1, 2019, and April 6, 2020 | DCC-GARCH | The two largest cryptocurrencies are suitable as short-term safe havens. Their daily returns tend to be negatively correlated with the S&P500 during the pandemic. |

July 10, 2020, based on the European Union Council’s announcement on June 30th of the gradual lifting of temporary restrictions on non-essential travel to European countries. To capture the full impact of this decision in different markets, we collected data for ten days after that announcement.

3.2. Methodology

Following Guedes et al. (2019) our analysis was conducted in two stages. In the first stage, we computed the price efficiency of each asset class under consideration using a multifractal detrended fluctuation analysis (MF-DFA). The correlations among them were then estimated using a detrended partial-cross-correlation analysis (DPCCA). These methodological approaches are described below.

3.3. Multifractal detrended fluctuation analysis (MF-DFA)

Financial time series are functionally complex systems that have predominantly nonlinear temporal dynamics (Tsay, 2010). They are especially sensitive to external disturbances, making it very difficult to forecast their future behaviors. In recent years, researchers have started to apply nonlinear methodological approaches to analyze these behaviors. One such approach that has found increasing use is the MF-DFA, which allows researchers to measure the long-term efficiency of price returns. MF-DFA has been widely used to measure the efficiency of stock markets (Zunino et al., 2008; Onali and Goddard, 2009; Wang et al., 2009; Liu et al., 2010; Stavroyiannis et al., 2010; Horta et al., 2014; Jin, 2016; Al-Yahyaee et al., 2018; Tiwari et al., 2019; Maganini et al., 2018).

Multifractals are complicated self-similar objects consisting of differently weighted fractals of various non-integer dimensions. Thus, a multifractal system is a generalization of a fractal system in which a single scaling exponent does not sufficiently describe its dynamics (Dutta et al., 2013). In recent years, several methodological approaches have been developed for the specific purpose of studying multifractality in time series data. The best known of these approaches is MF-DFA (Salat et al., 2017), in particular the detailed six-step process proposed by Kantelhardt et al. (2002). The measurement of multifractality in MF-DFA is based on the Hurst exponent, which ranges from 0 to 1.0. A Hurst exponent between 0 and 0.5 means that a time series has an anti-correlated structure and between 0.5 and 1.0 means that a time series has a long-range dependence (i.e., it is correlated). In the special case when the Hurst exponent is equal to 0.5, the time series has an independent or short-range dependent structure (random walk behavior) (Ihlen, 2012).

The degree of multifractality is expressed as Δh = h(qmin) - h(qmax), where the exponent h(q) is known as the generalized Hurst exponent; the smaller the Δh coefficient, closer to 0.5 are the range of the Hurst exponents. A price series is considered efficient if a time series of those prices follow a random walk. The closer the Hurst exponent is to 0.5, the more anti-correlated the values in time series. The smaller the value of Δh, the closer the Hurst exponent is to 0.5; therefore, small values of Δh indicate efficiency in the time series.
An alternative quantifier for the degree of multifractality is the width \( \Delta \alpha \) (intermittency degree) of the singularity spectrum \( \alpha \). The parameter \( \alpha \) is the Hölder exponent or singularity strength, while \( f(\alpha) \) is the fractal dimension of the subset of the time series with singularities of strength equal to \( \alpha \). The lower the values of the \( \Delta h \) and \( \Delta \alpha \) coefficients, the higher the efficiency of the time series (Zunino et al., 2008; Wang et al., 2009).

### 3.4. Detrended partial cross-correlation analysis (DPCCA)

Researchers have used different methodological approaches to measure the correlation between two time series. Perhaps the most popular is the Pearson coefficient; however, this coefficient is not always robust (Wilcox, 2005) and can be misleading if outliers are present, as in real-world financial data characterized by a high degree of nonstationarity (Devlin et al., 1975). It has been shown that time series data exhibit complex and dynamic behaviors whose autocorrelation (the cross-correlation of the signal with itself) can be characterized by power laws (Moret et al., 2003). Hurst was one of the first to identify a power law in a time series in the real world, specifically studying the Nile River and problems related to water storage using rescaled (R/S) statistics (Hurst, 1951). An alternative method, DFA, was proposed to detect long-range autocorrelations embedded in the mosaic structure of DNA because it avoids the spurious detection of apparent long-range autocorrelations (Peng et al., 1994). The DFA method performs better than the R/S standard in quantifying the scaling behavior of noisy signals across a wide range of correlations (Hu et al., 2001; Chen et al., 2002).

Several variations of the DFA method have been developed to analyze long-range correlations and identify price efficiency in time series. MF-DFA, as proposed by Kantelhardt et al. (2002), is one such widely used approach in the literature. Using the DFA approach, techniques have been developed to analyze cross-correlations between two time series. One such technique is detrended cross-correlation analysis (DCCA) as proposed by Podobnik and Stanley (2008), which is designed to investigate power law cross-correlations between time series of equal length \( N \) recorded simultaneously in the presence of nonstationarity. Podobnik and Stanley (2008) demonstrated DCCA’s usefulness by applying it to problems in physics, physiology, and finance. For example, they reported power law cross-correlations in the absolute values of logarithmic changes in price between the Dow Jones and NASDAQ stock market indices. Yuan et al. (2015) proposed the DPCCA, which improves on DCCA by incorporating the partial correlation technique and is therefore useful in quantifying multi-signal correlations in a complex system. DPCCA is useful for extracting long-term intrinsic power law cross-correlations between two non-stationary signals. A key advantage of these methods over traditional approaches is that they can analyze changes in correlations over time. Another advantage is that they are useful for analyzing complex non-stationary real-world systems. During the last few years, DPCCA has been applied in a number of different areas, such as climate studies (Piao et al., 2016; Yuan et al., 2016), medical research (Ide et al., 2017; Chen et al., 2018), biology (Ezenwa et al., 2016), and finance (Lin et al., 2018; Lima et al., 2019; Ferreira et al., 2019; and Guedes et al., 2019).

Following Yuan et al. (2015) we calculated partial cross-correlation coefficients at different temporal scales. Implementing DPCCA for \( m \) temporal series of length \( N \), \( x_i(t) \), \( i = 1, \ldots, m; k = 1, \ldots, N \) consists of inverting a matrix of DCCA cross-correlation coefficients calculated at scale \( n \):

\[
\rho(n) = \begin{pmatrix}
\rho_{1,1}(n) & \rho_{1,2}(n) & \cdots & \rho_{1,m}(n) \\
\rho_{2,1}(n) & \rho_{2,2}(n) & \cdots & \rho_{2,m}(n) \\
\vdots & \vdots & \ddots & \vdots \\
\rho_{m,1}(n) & \rho_{m,2}(n) & \cdots & \rho_{m,m}(n)
\end{pmatrix}
\]

(1)

where \( \rho_{ij}(n) = \frac{F^2_{ij}(n)}{F_i(n)F_j(n)} \), \( i, j = 1, \ldots, m \). \( F^2_{ij}(n) \) is the detrended covariance between two series obtained by DCCA, and \( F_i(n) \) and \( F_j(n) \) are DFA fluctuation functions of the individual series. The inverse matrix

\[
C(n) = \begin{pmatrix}
C_{1,1}(n) & C_{1,2}(n) & \cdots & C_{1,m}(n) \\
C_{2,1}(n) & C_{2,2}(n) & \cdots & C_{2,m}(n) \\
\vdots & \vdots & \ddots & \vdots \\
C_{m,1}(n) & C_{m,2}(n) & \cdots & C_{m,m}(n)
\end{pmatrix}
\]

(2)

is then used to calculate partial cross-correlation coefficients:

### Table 2

Descriptive statistics for the return series Bitcoin (BTC), gold, a US dollar index (US), and the MSCI World index from March 11 to July 10, 2020.

|           | BTC    | Gold   | MSCI   | US     |
|-----------|--------|--------|--------|--------|
| Mean      | 7.29E-06 | 4.27E-06 | 6.42E-06 | -7.49E-08 |
| Median    | 3.97E-05 | 1.46E-05 | 0.0000 | 0.0000 |
| Maximum   | 0.1309  | 0.0152  | 0.0351 | 0.0077 |
| Minimum   | -0.1268 | -0.0112 | -0.0526 | -0.0526 |
| Std. Dev. | 0.0040  | 0.0009  | 0.0012 | 0.0003 |
| Skewness  | -2.0488 | -0.13712 | 7.2047 | -0.4095 |
| Kurtosis  | 204.546 | 13.704  | 451.695 | 26.879 |
| Observations | 21,093 | 21,093 | 21,093 | 21,093 |
that quantify intrinsic cross-correlations among series \( i \) and \( j \), at each time scale \( n \), when the influence of other signals are eliminated (Yuan et al., 2015). If the two series are not cross-correlated, \( \rho_{\text{DPCCA}}(n) \) oscillates about 0 (bounded by −1.0 and 1.0 for perfect negative and perfect positive cross-correlation, respectively), while for anti cross-correlated series \( \rho_{\text{DPCCA}}(n) \) is strictly negative and for positively cross-correlated series \( \rho_{\text{DPCCA}}(n) \) is positive.

\[ \rho_{\text{DPCCA}}(i,j;n) = \frac{-C_{i,j}(n)}{C_i(n)C_j(n)}, \quad i,j = 1, \ldots, m. \] (3)

4. Data and preliminary statistics

Our analysis used intraday price data at 5-minute intervals for Bitcoin, gold, the MSCI World index, and the US dollar index for the period March 11, 2020, through July 10, 2020, available from the Refinitiv Market Data. Table 2 shows descriptive statistics for the analyzed return series. Calculating the DPCCA coefficients requires two time series of equal length. Therefore, we filtered the data to obtain the days and times when all four of our time series had values available. The final sample consisted of 21,093 logarithmic returns for each time series.

Table 2 shows that Bitcoin had the highest intraday return, which varied by as much as 13.09% over a 5-minute interval. Bitcoin also suffered the largest decline in a 5-minute interval, dropping by 12%. The skewness values show that the asymmetry in returns was highest for the MSCI index (−7.2047) and lowest for gold (−0.1371). Fig. 1 shows a large decline in all prices over the first 5000 data points (equal to approximately 1 month, quoted every 5 min) after the WHO declared COVID-19 to be a pandemic; then, there is a gradual process of adjustment in prices. Fig. 1 also shows a greater tendency toward volatility clusters for the Bitcoin and MSCI return series than for gold and the US dollar.

5. Results

5.1. Price Efficiency during the pandemic crisis

The results of our MF-DFA analysis are presented in Table 3. The efficiency of each price series is assessed using two indicators, \( \Delta h \) and \( \Delta \alpha \). The lower the values of \( \Delta h \) and \( \Delta \alpha \), more efficient is the time series analyzed (Wang et al., 2009; Sensoy and Tabak, 2016; Silva Filho et al., 2018; Diniz-Maganini et al., 2021). Table 3 shows that price returns for gold have the lowest \( \Delta h \) value (0.3089), followed by Bitcoin (0.3925), the US dollar index (0.4403), and the MSCI World index (0.7609). The values of \( \Delta \alpha \), which vary between 0.4599 and 0.9299, are also lower for Bitcoin and gold compared to the US dollar and the MSCI World index. Together, these results indicate that the prices of gold and Bitcoin are closer to a random walk than the prices of the US dollar and MSCI World indices over the period we analyzed. Fig. 2 provides a graphical representation of these results.

In Fig. 2, the graph on the left shows the generalized Hurst exponent, and the graph on the right shows the intermittency degree of the multifractal spectrum for each time series. The red, blue, green, and light blue lines representing the prices of Bitcoin, gold, the MSCI World index, and the US dollar index, respectively, show that the greatest variations in the value of \( h(q) \) are generated by the MSCI World (green) and US dollar indices (light blue). The graph on the right shows the maximum and minimum values for the parameter \( \alpha \) for each of the time series. The width of the parabola (the difference between the maximum and minimum values for the \( \alpha \) parameter) is an indicator of the multifractal behavior of the data and also of the efficiency of the financial time series, that is, wider the parabola, the less efficient the time series. Fig. 2 shows that the parabolas are widest for the MSCI and US dollar indices and lowest for Bitcoin and gold. Thus, we conclude that the time series of prices for gold and Bitcoin demonstrate relatively high levels of price efficiency compared to the US dollar and MSCI World indices, which show somewhat lower levels of efficiency. In the next stage of the analysis, we analyze whether the prices of these assets behaved like “safe havens” relative to each other.

5.2. Cross-Correlations between time series during the pandemic crisis

Given that a safe haven is an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil, we examined the strength of the cross-correlations among the four time series using different time scales. These results are presented in Fig. 3, which shows the DPCCA coefficients \( \rho_{\text{DPCCA}}(n) \) (see Yuan et al., 2015) for the correlations between Bitcoin and the US dollar and MSCI World indices as well as for gold and the US dollar and MSCI World indices.

|            | \( \Delta h \) | \( \Delta \alpha \) |
|------------|----------------|-------------------|
| Bitcoin    | 0.3925         | 0.5223            |
| Gold       | 0.3089         | 0.4599            |
| US dollar index | 0.4403  | 0.6257            |
| MSCI       | 0.7609         | 0.9299            |
Fig. 2. Generalized Hurst exponents and multifractal spectra of intraday (5 min) returns for Bitcoin (BTC), gold (Gol), a US dollar index (USi), and the MSCI World index (MSC) from March 11, 2020, to July 10, 2020.

Fig. 3. DPCCA coefficients $\rho_{DPCCA}(n)$ across financial time series for Bitcoin (BTC), gold, a US dollar index, and the MSCI World index at different time scales. The DPCCA coefficient $\rho_{DPCCA}(n)$ quantifies the strength of the net cross-correlation between two time series at time scale $n$. 
Panel A shows the DPPCCA coefficients for Bitcoin price returns versus the US dollar and MSCI World indices; Panel B shows the coefficients for gold price returns versus the US dollar and MSCI World indices. Clearly, all of the DPPCCA coefficients vary across time scales. According to Lin et al. (2018), when DPPCCA coefficients at different time scales are below 0.3 and some values are close to zero, it implies that these pairs of correlations between markets are weak and are strongly influenced by other markets. From the first graph in Panel A, we can see that the net cross-correlation values between Bitcoin and the US dollar index fall in a range between just over −0.2 and approximately 0.3, regardless of the time scale. The fact that they hover around 0 suggests that the net cross-correlation of Bitcoin and the US dollar index is weak and strongly influenced by other markets.

The second graph in Panel A shows the net correlations between Bitcoin and the MSCI World index, and the graphs in Panel B present the net correlations of gold with the US dollar and MSCI World indices, respectively. In all three cases, the DPPCCA coefficients appear to behave as monotonically decreasing functions of the time scale, that is, they decrease as the time scale increases. When the time scale is \((n) > 15000\) (equating to approximately three months of prices quoted every five minutes), Bitcoin can be considered as a safe haven relative to MSCI and when the time scale \((n) > 10000\) (approximately two months quoted every five minutes), gold can be considered a safe haven relative to both the US dollar and MSCI World indices because the correlations between Bitcoin and the MSCI World index fall to −0.4 and for gold relative to both the US dollar and MSCI World indices decline to approximately −0.6 for those longer time scales.

Taken together, the results of our analysis indicate the following. First, both Bitcoin and gold can be considered as safe havens for investors in the MSCI World index, but only gold can be considered a safe haven against the US dollar exposure. Second, the safe haven properties observed for Bitcoin and gold are a function of the time scale considered. Third, gold’s safe haven property appears to be stronger than Bitcoin’s.

6. Discussion and conclusions

At the time this study was conducted, the COVID-19 pandemic continued to ravage most countries of the world, with little sign of abating a full year after the outbreak. The pandemic has inflicted enormous economic damage globally, caused more than a million deaths, and brought activities of daily life to a standstill in the most affected areas. We remain apprehensive about the eventual economic impact of the crisis, including the impact on financial markets (Goodell, 2020). We analyzed the price behaviors of Bitcoin, gold, the US dollar index, and the MSCI World index during the most critical period of the pandemic to understand their potential safe haven properties. Our results suggest that gold and Bitcoin have greater price efficiency than the MSCI World and US dollar indices and also appear to act as safe havens relative to the US dollar and global developed equity markets.

During the first four months of the crisis caused by the COVID-19 pandemic, when relatively short time scales are considered, the net cross-correlations between these assets are relatively weak. When longer time scales are considered, the net cross-correlations are negative and substantially higher. Gold exhibits high negative cross-correlations with both the US dollar and MSCI World indices, whereas Bitcoin shows high negative cross-correlations only against the MSCI World index. Thus, it appears that gold has stronger safe haven properties than Bitcoin. However, our results may not warrant generalizations as prior research clearly shows that results can be highly dependent on the time frames of the analyses. While our results offer preliminary evidence that Bitcoin may have safe haven properties, additional studies involving longer time periods and additional asset classes are necessary before we can draw any strong conclusions on this issue. Therefore, expectations of the potential value of Bitcoin and its benefits to financial market participants should be moderated (Corbet et al., 2019). Our results suggest that Bitcoin may serve as safe haven during periods of extreme economic stress and turmoil but not as effectively as gold as per the analysis of both assets’ price behaviors during the first four months after the pandemic outbreak.

Author statement

Natalia Diniz-Maganini: Writing-Original Draft Preparation, Methodology, Software, Data Curation, Writing-Reviewing, Investigation. Eduardo H. Diniz: Writing-Original Draft Preparation, Writing-Reviewing. Abdul A. Rasheed: Supervision, Writing, Writing-Reviewing, Editing, Validation.

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