The Quarterly Review of Economics and Finance 82 (2021) 71–85

Contents lists available at ScienceDirect

The Quarterly Review of Economics and Finance

journal homepage: www.elsevier.com/locate/qref

Hedge and safe haven properties during COVID-19: Evidence from Bitcoin and gold

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A R T I C L E I N F O

Article history:
Received 18 March 2021
Received in revised form 12 July 2021
Accepted 14 July 2021
Available online 5 August 2021

JEL classification:
G11
G15
G23

Keywords:
Bitcoin
DCC
Hedge
Gold
Safe haven

A B S T R A C T

The COVID-19 pandemic has caused an unprecedented human and health crisis. The measures taken to contain the damage caused a global economic slowdown. Investors face liquidity pressures resulting from the general downturn in the financial markets, and might change their risk appetite. This paper reassesses the safe haven property of gold as a traditional asset, and Bitcoin which is gradually imposing itself as a new class of asset with unique characteristics. The empirical results, applied on major world stock market indices and currencies, and based on the multivariate asymmetric dynamic conditional correlation model, show the effectiveness of Bitcoin and gold as hedging assets in reducing the risk of international portfolios. Moreover, the analysis provides evidence that during the COVID-19 pandemic, gold is a weak safe haven for the considered assets, while Bitcoin cannot provide shelter due to its increased variability.

1. Introduction

The COVID-19 pandemic has succeeded in looting and destabilizing the entire world. In just few months, it endangered not only lives, but also economic borders, global businesses and the very essence of the world's financial equilibrium. This crisis caused the closure of borders, a sharp slowdown in the global economy and a stock market crash on March 11, 2020. Consequently, many investors turned to uncorrelated assets to hedge their portfolios in order to cope with the crisis and support the recovery.

Throughout its history, gold has been viewed as a value store, portfolio stabilizer and source of liquidity in times of financial turbulence. Gold is known as a hedge against inflationary pressures in the U.S. and U.K. (Hoang, Lahiani, & Heller, 2016). It reacts countercyclically to macroeconomic news (Elder, Miao, & Ramchander, 2012) and works differently from other assets, especially stocks. When prices of stock market indices plummet, gold retains its value. Its effectiveness as a hedge and safe haven against equities in different markets is well confirmed by numerous studies (e.g., Baur & Lucey, 2010; Beckmann, Berger, & Czudaj, 2015, among others).

However, Baur and Glover (2012) showed that investor behavior can destroy the hedging potential of gold due to increased investment in the precious metal for hedging and speculation purposes. For example, Klein (2017) used a dynamic correlation model to show that precious metals had a hedging role for stock market indices in American and European countries; nevertheless, this role have dissipated after 2013.

Over the past decade, attention has shifted from gold to a new asset, Bitcoin. Bitcoin was first introduced in 2009 in the wake of the bankruptcy of Lehman Brothers investment bank, as the confidence in financial institutions deteriorated. Soon after, this cryptocurrency succeeded in catching the attention of investors and institutional bodies. It has established itself through its innovative character. The Bitcoin protocol is based on the voluntary participation of the parties, it is not subject to any control and allows everyone to accumulate and transfer value in a currency that resists price manipulation by central banks and global financial institutions (Chemkha, BenSaïda, & Ghorbel, 2021).

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https://doi.org/10.1016/j.qref.2021.07.006
1062-9769/

Obviously, this has led Bitcoin and gold to compete for the status of the most effective protective asset. Compared to gold, Bitcoin must overcome several challenges, particularly in terms of history, acceptance, consumption, intrinsic value and low volatility. However, gold and Bitcoin share several characteristics. (i) First, they both escape political influence and are regulated like commodities, especially in the U.S. where Bitcoin is considered a commodity by the CFTC institution. (ii) Second, no central authority intervenes to adjust or control their mining transactions and activities (Baur, Hong, & Lee, 2018); therefore, they are both independent from inflation. (iii) Third, both assets have a finite supply, and it is this scarcity that makes them valuable. Since Bitcoin's number of units in circulation is limited to 21 million, making it an anti-inflationary asset, which brings it closer to gold. (iv) Fourth, the asymmetric reaction to positive and negative news characterizes both Bitcoin (Bouri, Jalkh, Moln'ar, & Roubaud, 2017) and gold (Baur & Glover, 2012).

Researches on the link between the prices of gold and those of other assets, and the potential for hedge and safe haven continue to grow remarkably. Indeed, Bitcoin's low correlation with traditional assets makes it desirable for diversification (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Guesmi, Saadi, Abid, & Ftiti, 2019; Ji, Bouri, Gupta, & Roubaud, 2018), and a valuable hedge against stock markets (Baur et al., 2018; Dyhrberg, 2016) and commodities (Bouri et al., 2017). Furthermore, several studies claim that Bitcoin was not affected by the European debt crisis nor the Cypriot banking crisis, yet it prospered (Luther & Salter, 2017).

The economic impact of the COVID-19 crisis on financial markets has recently become a topic of interest. This has reignited the debate over whether the cryptocurrency has the ability to mimic or beat gold hedging and safe haven property against stocks. Moreover, to the best of our knowledge, a limited number of studies have analyzed Bitcoin and gold (Bouri et al., 2017; Corbet et al., 2018; Dyhrberg, 2016) without a comparable study between their roles against financial assets. To fill the gap in the literature, our study draws new insights into the potential of Bitcoin and gold to hedge against fluctuations in financial markets and their role as safe haven during the COVID-19 virus outbreak.

The remainder of this paper is organized as follows. Section 2 is a brief review of the literature. Section 3 explains the methodological approach. Section 4 describes the data sample. Section 5 analyzes the empirical results. Section 6 concludes.

2. Literature review

Since the global financial crisis of 2007-2009, there has been a resurgence of interest among academics and practitioners to study the hedge and safe haven potential of various asset classes against market downturns. Indeed, during times of crisis, investors seek to dispose of their risky assets in favor of other more secure assets (*flight-to-safety*). This is precisely the case of gold, whose value does not depend on a company's performance nor a state's ability to repay its debt. Thus, when other assets collapse, one can always rely on gold, since it can be easily resold when needed.

Lawrence (2003) provides an overview of the evolution of the relationship between gold and stock markets. The author concludes that gold appears to be isolated from the business cycle – unlike other commodities – which may make it more attractive as a diversifier and even as a safe haven. Previous studies (Fleming, Kirby, & Ostdiek, 1998, among others) show evidence in favor of government bonds providing equity investors with a safe haven in times of crisis. Chan, Treepongkaruna, Brooks, and Gray (2011) show that U.S. Treasuries are a safe haven for equity investors during times of market stress. Flavin, Morley, and Panopoulou (2014) show that 1-year and 10-year U.S. treasury bonds, in addition to gold, are safe havens to protect portfolios in the event of a market downturn. However, even with some of the advantages associated with investing in Treasuries, there are still drawbacks to be aware of, such as the low yield.

Other investors, looking for an alternative to gloomy financial markets, prefer the asset backed securities (ABS), a type of fixed income assets that offer safe returns against market turmoil. Bernanke, Bertaut, DeMarco, and Kamin (2011) show that ABS have become an attractive alternative for investors, offering returns slightly higher than those of Treasuries. However, these types of ABS collateral have proven to be risky (Gennaioli, Martin, & Rossi, 2018), involving risk of asset devaluation, and can have serious consequences, such as an increase in defaults during the U.S. born subprime mortgage crisis in 2007 (Bertaut, DeMarco, Kamin, & Tryon, 2012).

Unlike risk-free assets, gold has naturally been considered as a safe haven given its historical role as a natural currency and a value store. It is negatively correlated with the financial cycle, so it tends to provide positive returns during crises (Bouri, Lucey, & Roubaud, 2020). There is a vast literature studying the potential of gold as a hedge and a safe haven, but the results are mixed. For instance, based on data from major emerging and developing countries, Baur and McDermott (2010) discuss whether gold is truly safe. Their results confirm this property of gold for American and European stock indices but not for other markets. Hood and Malik (2013) find that gold is a hedge for the U.S. stock market, but its safe haven property is low relative to the volatility index. Beckmann et al. (2015) show that gold serves both as a hedge and as an effective safe haven. Lucey and Li (2015) study the role of precious metals as safe havens in a time varying framework and find that the strength of gold as a safe haven changes over time. For emerging countries, Chkili (2016) examines the relationship between gold and the stock markets of BRICS countries and suggests that gold can serve as a safe haven against extreme movements. Likewise, Akhtaruzzaman, Boubaker, Lucey, and Sensoy (2021) examine the role of gold as a safe haven during the COVID-19 crisis. They found that during phase I (before March 16, 2020) gold was a strong safe haven; however, its property has weakened during phase II starting from March 17, 2020.

Bitcoin is another popular asset that has succeeded in gaining the attention of investors as a safe haven. Bouoiyour and Selmi (2017) admit that Bitcoin has both the hedge and safe haven properties for the U.S. stock index. They also demonstrate that precious metals have lost their safe haven property over time. Bouri, Lucey, et al. (2020) find that cryptocurrencies can be used as a hedge against the downside risk of equity investments. This property applies during normal periods and times of crisis. Several researchers suggest that the role of Bitcoin as a safe haven and hedging instrument is quite limited (Eisl, Gasser, & Weinmayer, 2015, among others). For example, based on an asymmetric dynamic conditional correlation (A-DCC) model, Bouri et al. (2017) state that Bitcoin offers diversification advantages over various other assets, such as stock indices, bonds, oil, gold, commodity indices, and the U.S. dollar, but its use as hedge or safe haven only appears in certain cases which differ from one horizon to another. Klein, Pham Thu, and Walther (2018) suggest that Bitcoin is not a safe haven and cannot hedge against risk, even for developed markets. Shahzad, Bouri, Roubaud, Kristoufek, and Lucey (2019) find that gold has an "indisputable" safe haven property compared to that of Bitcoin. While gold is an effective safe haven for all G7 stock indices, Bitcoin only offers a safe haven role for the Canadian stock index. Likewise, Conlon and McGee (2020) show that Bitcoin does not act as a safe haven. It is evolving at the same rate as the S&P 500 as the health crisis develops.

The aforementioned studies on the characteristics of gold and Bitcoin offer mixed results. Therefore, it becomes essential to reassess the hedge and safe haven properties of Bitcoin in the recent context of COVID-19; and to test whether gold retains its characteristic as a stable value store that can protect investors, policymakers and regulators from the adverse effects of the pandemic.

3. Methodology

To analyze whether Bitcoin and gold can serve as a hedge or safe haven for the main traditional assets of developed markets, our methodology is based on the principles presented by Baur and Lucey (2010). The methods quickly gained popularity and have been applied in various studies, for example, on credit default swaps, bonds, metals and gold (Ciner, Gurdgiev, & Lucey, 2013; Li & Lucey, 2017; Lucey & Li, 2015).

Baur and Lucey (2010) provide clear definitions and distinction of diversifier, hedge, and safe haven. An asset is classified as *diversifier* if it is positively, but weakly correlated, with another asset or portfolio on average. A *hedge* is an asset that is uncorrelated (weak hedge) or negatively correlated (strong hedge) with another asset or portfolio on average. A hedge may not reduce losses during times of market stress or turbulence, as the asset may show positive correlations with other assets during some periods, and negative correlations during other periods, resulting in a negative correlation on average. A *safe haven* is an asset that is uncorrelated (weak safe haven) or negatively correlated (strong safe haven) with another asset or portfolio in times of turmoil. Thus, a safe haven investment has the potential to protect investors and offset losses in the event of market crises, such as the COVID-19 pandemic.

3.1. The asymmetric DCC model

Several studies in finance use the multivariate dynamic conditional correlation (DCC) model of Engle (2002) to investigate the correlations between assets, and to construct reliable hedging strategies (Bouri et al., 2017; Chang, McAleer, & Tansuchat, 2011; Ciner et al., 2013, among others). The DCC model provides a simple framework for extracting dynamic correlations for multiple assets in a sparse parameter configuration. In this paper, we extend the analysis by employing the asymmetric dynamic conditional correlation (A-DCC) model of Cappiello, Engle, and Sheppard (2006), which identifies the asymmetric responses in the conditional variances and correlations during stress periods. The asymmetry, also called "leverage effect", detects an often observed stylized fact of financial assets where an unexpected drop (bad news) in asset prices tends to increase the volatility more than an unexpected rise (good news) with the same magnitude (BenSaïda, 2019, 2021).

3.1.1. The model

Let $\boldsymbol{r}_t$ be a $(n \times 1)$ vector of returns of n assets, such that $\boldsymbol{r}_t = \left[r_{1,t}, \ldots, r_{n,t}\right]'$. For the bivariate case, $n = 2$, the vector $\boldsymbol{r}_t$ contains the returns $r_{1,t}$ of the Bitcoin (or gold), and $r_{2,t}$ of a stock market index (or exchange rate). The returns follow a n-variate Student's t_ν distribution with ν degrees-of-freedom as in Eq. (1).

$$\begin{aligned} \boldsymbol{r}_t = &\ \boldsymbol{\mu}_t + \boldsymbol{\varepsilon}_t \\ \boldsymbol{r}_t | I_{t-1} \sim &\ t_{n,\nu}\left(\boldsymbol{\mu}_t, \boldsymbol{H}_t\right) \end{aligned} \tag{1}$$

where $\boldsymbol{\mu}_t$ stands for the conditional mean vector that may include a constant and/or past observations. The mean equation of the A-DCC model is specified as an autoregressive moving average (ARMA) process, as debated by Kyrtsou and Labys (2007), since overlooking this characteristic may undermine some of the dynamics of the relationships between the studied variables. The term $\boldsymbol{H}_t$ is the conditional covariance matrix of $\boldsymbol{r}_t$; and $\boldsymbol{\varepsilon}_t$ denotes a $(n \times 1)$ vector of residuals conditional on the information set I_{t-1} defined at time $t-1$. The general dynamic correlation model of the A-DCC is defined in Eq. (2).

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t \tag{2}$$

where $\boldsymbol{R}_t$ represents the time varying conditional correlation matrix, and $\boldsymbol{D}_t$ stands for the $(n \times n)$ diagonal matrix containing the conditional standard deviations of univariate GARCH-type models, such that:

$$\begin{aligned} \boldsymbol{D}_t = &\ \operatorname{diag}\left(h_{1,t}^{1/2}, \ldots, h_{n,t}^{1/2}\right) \\ \boldsymbol{R}_t = &\ \operatorname{diag}(\boldsymbol{Q}_t)^{-1/2}\, \boldsymbol{Q}_t \operatorname{diag}(\boldsymbol{Q}_t)^{-1/2} \end{aligned} \tag{3}$$

The term $\boldsymbol{Q}_t$ is a positive definite matrix that represents the evolution of the conditional correlation of the standardized residuals $\boldsymbol{z}_t$. Where, $\boldsymbol{z}_t$ denotes a $(n \times 1)$ random vector of independent and identically distributed (*i.i.d.*) errors (Engle, 2002), as in Eq. (4). Note that $\boldsymbol{z}_t$ are the residuals standardized by their conditional standard deviation (Engle & Sheppard, 2001).

$$\begin{aligned} \boldsymbol{z}_t &= \boldsymbol{D}_t^{-1}\left(\boldsymbol{r}_t - \boldsymbol{\mu}_t\right) \\ \boldsymbol{z}_t &\overset{i.i.d.}{\sim} t_{n,\nu}\left(\boldsymbol{0}, \boldsymbol{R}_t\right) \end{aligned} \tag{4}$$

It follows from this specification that $\mathbb{E}_{t-1}\left(\boldsymbol{z}_t \boldsymbol{z}_t'\right) = \boldsymbol{D}_t^{-1} \mathbb{E}_{t-1}\left(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'\right) \boldsymbol{D}_t^{-1} = \boldsymbol{D}_t^{-1} \boldsymbol{H}_t \boldsymbol{D}_t^{-1} = \boldsymbol{R}_t$. A typical element of $\boldsymbol{R}_t$ will have the form $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\ q_{jj,t}}}$, such that $\boldsymbol{Q}_t = \left\{q_{ij,t}\right\}_{i,j=1}^{n}$.

Each conditional variance $h_{i,t}$ of an asset i, for $i = \left\{1, \ldots, n\right\}$, is estimated using the univariate asymmetric Threshold GARCH (TARCH) model of Zakoian (1994). The TARCH model of orders (1,1) is represented in Eq. (5).

$$\begin{cases} r_{i,t} = & c_i + \phi_{i,1} r_{i,t-1} + \varepsilon_{i,t} \\ \varepsilon_{i,t} = & z_{i,t}\sqrt{h_{i,t}}, \text{ with } z_{i,t} \overset{i.i.d}{\sim} t(\nu_i) \\ \sqrt{h_{i,t}} = & \omega_i + \alpha_{i,1}\left|\varepsilon_{i,t-1}\right| + \beta_{i,1}\sqrt{h_{i,t-1}} + \gamma_{i,1} \mathbb{1}_{[\varepsilon_{i,t-1}<0]} |\varepsilon_{i,t-1}| \end{cases} \tag{5}$$

where c_i indicates a drift term, $\phi_{i,1}$ is the autoregressive coefficient of order 1 in the mean equation. Alternatively, $r_{i,t} = \mu_{i,t} + \varepsilon_{i,t}$. In the variance equation, ω_i is a constant term, $\alpha_{i,1}$ detects the ARCH effect, $\beta_{i,1}$ captures the persistence of the volatility process, and $\gamma_{i,1}$ represents the asymmetric coefficient. The indicator function $\mathbb{1}_{[\varepsilon_{i,t}<0]}$ equals 1 if $\varepsilon_{i,t} < 0$ and 0 otherwise. The coefficients must satisfy the positivity conditions $\omega_i > 0$, $\alpha_{i,1}$, $\beta_{i,1} \geqslant 0$ and $\alpha_{i,1} + \gamma_{i,1} \geqslant 0$, and the stationarity condition $\alpha_{i,1} + \beta_{i,1} + \frac{1}{2}\gamma_{i,1} < 1$. The error terms $z_{i,t}$ are *i.i.d.* with zero mean and unit variance and assumed to follow a standard Student's t distribution with ν_i degrees-of-freedom. For this specification, a positive value of $\gamma_{i,1}$ indicates that negative conditional residuals tend to increase the volatility more than positive shocks of the same magnitude.

The dynamics of $\mathbf{Q}_t$ for the A-DCC(p, q) model is illustrated in Eq. (6).

$$\begin{aligned} \mathbf{Q}_t = \overline{\mathbf{Q}} + \sum_{i=1}^{p} a_i\left(\boldsymbol{z}_{t-i}\boldsymbol{z}_{t-i}' - \overline{\mathbf{Q}}\right) + \sum_{j=1}^{q} b_j\left(\mathbf{Q}_{t-j} - \overline{\mathbf{Q}}\right) \\ + \sum_{i=1}^{p} g_i\left(\boldsymbol{z}_{t-i}^{-}\boldsymbol{z}_{t-i}^{-'} - \overline{\boldsymbol{N}}\right) \end{aligned} \tag{6}$$

When the lag orders $p = 1$ and $q = 1$, the model can be reduced to A-DCC(1,1) of Cappiello et al. (2006) in Eq. (7),

$$\mathbf{Q}_t = (1 - a - b)\overline{\mathbf{Q}} - g\overline{\boldsymbol{N}} + a\boldsymbol{z}_{t-1}\boldsymbol{z}_{t-1}' + b\mathbf{Q}_{t-1} + g\boldsymbol{z}_{t-1}^{-}\boldsymbol{z}_{t-1}^{-'} \tag{7}$$

where a and b are non-negative scalars that capture the effects of previous shocks and previous conditional correlations, respectively, on the current conditional correlation. A necessary and sufficient condition for $\boldsymbol{Q}_t$ to be positive definite is that $a+b+\lambda_{\max} g<1$, where $\lambda_{\max}$ is the maximum eigenvalue of $\left[\overline{\boldsymbol{Q}}^{-1/2}\overline{\boldsymbol{N}}\overline{\boldsymbol{Q}}^{-1/2}\right]$. The term $\overline{\boldsymbol{Q}}$ is the unconditional covariance matrix of the standardized residuals $z_{i,t}=\frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}}$ such that $\overline{\boldsymbol{Q}}=\mathbb{E}\left(\boldsymbol{z}_t\boldsymbol{z}_t'\right)$. The parameter g denotes the asymmetric effect in the model. The quantity $\boldsymbol{z}_t^-=\mathbb{1}_{[\boldsymbol{z}_t<0]}\odot\boldsymbol{z}_t$, where $\odot$ is the Hadamard product, and $\mathbb{1}_{[\boldsymbol{z}_t<0]}$ is a $(n\times 1)$ indicator function that takes on value 1 when the argument $z_{i,t}<0, i=\left\{1,\ldots,n\right\}$ and 0 otherwise. The term $\overline{\boldsymbol{N}}=\mathbb{E}\left(\boldsymbol{z}_t^-\boldsymbol{z}_t^{-'}\right)$ represents the unconditional covariance matrix of $\boldsymbol{z}_t^-$.

In practice, the expectations of $\overline{\boldsymbol{Q}}$ and $\overline{\boldsymbol{N}}$ are infeasible; hence, they are replaced with the sample analogs $\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{z}_t\boldsymbol{z}_t'$ and $\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{z}_t^-\boldsymbol{z}_t^{-'}$, respectively.

3.1.2. Estimation

Following Engle (2002), the estimation of the A-DCC model is conducted using a two-step maximum likelihood method. (1) In a first step, we separately estimate the conditional variances using a univariate GARCH-type model for each time series in Eq. (5). (2) In a second step, we estimate the conditional correlation in Eq. (7).

The conditional joint distribution of the returns has the following form, where $\Gamma(\cdot)$ is the gamma function:

$$f_{n,\nu}\left(\boldsymbol{r}_t|I_{t-1}\right)=\left|\boldsymbol{H}_t\right|^{-\frac{1}{2}}\frac{\Gamma\left(\frac{\nu+n}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\left(\pi\left(\nu-2\right)\right)^{\frac{n}{2}}}\left(1+\frac{(\boldsymbol{r}_t-\boldsymbol{\mu}_t)'\boldsymbol{H}_t^{-1}(\boldsymbol{r}_t-\boldsymbol{\mu}_t)}{\nu-2}\right)^{-\frac{\nu+n}{2}} \quad (8)$$

Denote $\boldsymbol{\theta}$ the vector of parameters in $\boldsymbol{D}_t$, i.e., the parameters of all univariate conditional volatility models in Eq. (5); and $\boldsymbol{\phi}$ the vector of additional parameters in $\boldsymbol{R}_t$, i.e., the parameters of the conditional correlation model in Eq. (7). The log-likelihood function to maximize is written as:

$$L\left(\boldsymbol{\theta},\boldsymbol{\phi}\right)=\sum_{t=1}^{T}\ln f_{n,\nu}\left(\boldsymbol{r}_t|\boldsymbol{\theta},\boldsymbol{\phi},I_{t-1}\right) \quad (9)$$

$$\begin{aligned}
&=\sum_{t=1}^{T}\Bigg[\ln\Gamma\left(\frac{\nu+n}{2}\right)-\ln\Gamma\left(\frac{\nu}{2}\right)-\frac{n}{2}\left(\pi\left(\nu-2\right)\right)\\
&\quad-\frac{1}{2}\ln\left|\boldsymbol{H}_t\right|-\left(\frac{\nu+n}{2}\right)\ln\left(1+\frac{(\boldsymbol{r}_t-\boldsymbol{\mu}_t)'\boldsymbol{H}_t^{-1}(\boldsymbol{r}_t-\boldsymbol{\mu}_t)}{\nu-2}\right)\Bigg]\\
&=\sum_{t=1}^{T}\Bigg[\ln\Gamma\left(\frac{\nu+n}{2}\right)-\ln\Gamma\left(\frac{\nu}{2}\right)-\frac{n}{2}\left(\pi\left(\nu-2\right)\right)\\
&\quad-\ln\left|\boldsymbol{D}_t\right|-\frac{1}{2}\ln\left|\boldsymbol{R}_t\right|-\left(\frac{\nu+n}{2}\right)\ln\left(1+\frac{\boldsymbol{z}_t'\boldsymbol{R}_t^{-1}\boldsymbol{z}_t}{\nu-2}\right)\Bigg]
\end{aligned} \quad (9)$$

The likelihood function is divided into volatility term $L_v\left(\boldsymbol{\theta}\right)$ and correlation term $L_c\left(\boldsymbol{\theta},\boldsymbol{\phi}\right)$ in Eq. (10).

$$\begin{aligned}
L\left(\boldsymbol{\theta},\boldsymbol{\phi}\right)&=\sum_{t=1}^{T}\Bigg[n\ln\Gamma\left(\frac{\nu+1}{2}\right)-n\ln\Gamma\left(\frac{\nu}{2}\right)-\frac{n}{2}\left(\pi\left(\nu-2\right)\right)\\
&\quad-\ln\left|\boldsymbol{D}_t\right|-\frac{\nu+1}{2(\nu-2)}(\boldsymbol{r}_t-\boldsymbol{\mu}_t)'\boldsymbol{D}_t^{-2}(\boldsymbol{r}_t-\boldsymbol{\mu}_t)\Bigg]\\
&\quad+\sum_{t=1}^{T}\Bigg[\ln\Gamma\left(\frac{\nu+n}{2}\right)-n\ln\Gamma\left(\frac{\nu+1}{2}\right)+(n-1)\ln\Gamma\left(\frac{\nu}{2}\right)\\
&\quad-\frac{1}{2}\ln\left|\boldsymbol{R}_t\right|-\left(\frac{\nu+n}{2}\right)\ln\left(1+\frac{\boldsymbol{z}_t'\boldsymbol{R}_t^{-1}\boldsymbol{z}_t}{\nu-2}\right)+\frac{\nu+1}{2(\nu-2)}\boldsymbol{z}_t'\boldsymbol{z}_t\Bigg]\\
&=L_v\left(\boldsymbol{\theta}\right)+L_c\left(\boldsymbol{\theta},\boldsymbol{\phi}\right)
\end{aligned} \quad (10)$$

The likelihood function $L\left(\boldsymbol{\theta},\boldsymbol{\phi}\right)$ is maximized by separately maximizing $L_v\left(\boldsymbol{\theta}\right)$ in the first step, then, take the estimated coefficients $\hat{\boldsymbol{\theta}}$ as input for the second step to maximize $L_c\left(\hat{\boldsymbol{\theta}},\boldsymbol{\phi}\right)$. Following the development of Xu, Chen, Jiang, and Yuan (2018), under the multivariate t_ν distribution, the volatility part can be written as the sum of individual log-likelihoods in Eq. (11).

$$\begin{aligned}
L_v\left(\boldsymbol{\theta}\right)&=\sum_{t=1}^{T}\Bigg[n\ln\Gamma\left(\frac{\nu+1}{2}\right)-n\ln\Gamma\left(\frac{\nu}{2}\right)-\frac{n}{2}\left(\pi\left(\nu-2\right)\right)\\
&\quad-\ln\left|\boldsymbol{D}_t\right|-\frac{\nu+1}{2(\nu-2)}(\boldsymbol{r}_t-\boldsymbol{\mu}_t)'\boldsymbol{D}_t^{-2}(\boldsymbol{r}_t-\boldsymbol{\mu}_t)\Bigg]\\
&=\sum_{t=1}^{T}\Bigg[n\ln\Gamma\left(\frac{\nu+1}{2}\right)-n\ln\Gamma\left(\frac{\nu}{2}\right)-\frac{n}{2}\left(\pi\left(\nu-2\right)\right)\\
&\quad-\frac{1}{2}\sum_{i=1}^{n}\ln\left(h_{i,t}\right)-\frac{\nu+1}{2}\sum_{i=1}^{n}\frac{\left(r_{i,t}-\mu_{i,t}\right)^2}{(\nu-2)h_{i,t}}\Bigg]\\
&\approx\sum_{t=1}^{T}\sum_{i=1}^{n}\Bigg[\ln\Gamma\left(\frac{\nu_i+1}{2}\right)-\ln\Gamma\left(\frac{\nu_i}{2}\right)-\frac{1}{2}\ln(\pi(\nu_i-2))\\
&\quad-\left(\frac{\nu_i+1}{2}\right)\ln\left(1+\frac{\left(r_{i,t}-\mu_{i,t}\right)^2}{(\nu_i-2)h_{i,t}}\right)-\frac{1}{2}\ln\left(h_{i,t}\right)\Bigg]\\
&\approx\sum_{i=1}^{n}L_{v,i}\left(\boldsymbol{\theta}_i\right)
\end{aligned} \quad (11)$$

The maximization of $L_v\left(\boldsymbol{\theta}\right)$ is performed by separately maximizing the log-likelihood of each asset $L_{v,i}\left(\boldsymbol{\theta}_i\right)$ under the univariate Student's t distribution with ν_i degrees-of-freedom. The common degrees-of-freedom ν of the multivariate t_ν distribution is an approximation of each asset's degrees-of-freedom ν_i. Next, the correlation part is written as:

$$\begin{aligned}
L_c\left(\hat{\boldsymbol{\theta}},\boldsymbol{\phi}\right)&=\sum_{t=1}^{T}\Bigg[\ln\Gamma\left(\frac{\nu+n}{2}\right)-n\ln\Gamma\left(\frac{\nu+1}{2}\right)+(n-1)\ln\Gamma\left(\frac{\nu}{2}\right)\\
&\quad-\frac{1}{2}\ln\left|\boldsymbol{R}_t\right|-\left(\frac{\nu+n}{2}\right)\ln\left(1+\frac{\hat{\boldsymbol{z}}_t'\boldsymbol{R}_t^{-1}\hat{\boldsymbol{z}}_t}{\nu-2}\right)+\frac{\nu+1}{2(\nu-2)}\hat{\boldsymbol{z}}_t'\hat{\boldsymbol{z}}_t\Bigg]
\end{aligned} \quad (12)$$

where $\hat{\boldsymbol{z}}_t=\hat{\boldsymbol{D}}_t^{-1}\left(\boldsymbol{r}_t-\hat{\boldsymbol{\mu}}_t\right)$ are obtained from the estimation in the first step.[1]

The estimated coefficients from the two-step procedure are inefficient but consistent, since they are limited information estimators, as argued by Engle (2002).

3.2. Optimal portfolio weights

Portfolio optimization seems to be an important part of modern quantitative finance that solves most of the problems posed by investors through several alternatives. In this section, we compare the role of Bitcoin and gold as hedging tools for major international assets. In this context, investors seek to minimize the risk of their portfolios without reducing the expected returns. For this purpose, Kroner and Sultan (1993) introduced a method based on hedge ratios, which became widely applied in numerous empirical works (Akhtaruzzaman, Boubaker, Lucey, & Sensoy, 2021; Chang, McAleer, & Tansuchat, 2011; Chkili, 2016). This method determines

[1] Numerical estimations of the A-DCC model are conducted under R programming language using the `rugarch` package for univariate models in the first step, and `rmgarch` package for the correlation model in the second step. Both packages are available from https://cran.r-project.org/.

the optimal weight of Bitcoin (or gold) in a one-dollar wallet of asset at time t. The optimal weight is expressed in Eq. (13).

$$w_t^{i/(\mathrm{BTCorGLD})} = \frac{h_t^i - h_t^{i/(\mathrm{BTCorGLD})}}{h_t^i - 2h_t^{i/(\mathrm{BTCorGLD})} + h_t^{(\mathrm{BTCorGLD})}} \tag{13}$$

provided that,

$$w_t^{i/(\mathrm{BTCorGLD})} = \begin{cases} 0 & \text{if } w_t^{i/(\mathrm{BTCorGLD})} < 0 \\ w_t^{i/(\mathrm{BTCorGLD})} & \text{if } 0 \leqslant w_t^{i/(\mathrm{BTCorGLD})} \leqslant 1 \\ 1 & \text{if } w_t^{i/(\mathrm{BTCorGLD})} > 1 \end{cases}$$

where h_t^i and $h_t^{(\mathrm{BTCorGLD})}$ are the conditional volatilities of the selected market i and Bitcoin (or gold), respectively; and $h_t^{i/(\mathrm{BTCorGLD})}$ is the conditional covariance between Bitcoin (or gold) and the return of the asset i at time t. All the variances and covariances are extracted from the A-DCC model estimates. The weight of asset i in the one-dollar portfolio of Bitcoin (or gold) at time t equals $\left(1 - w_t^{i/(\mathrm{BTCorGLD})}\right)$.

3.3. Hedge ratio

In addition to the optimal portfolio allocation in the previous section, investors and market participants seek to minimize the risk of the hedged portfolio. One of the most used strategy is to compute the optimal hedge ratio (HR) based on multivariate GARCH-class models at time t in Eq. (14), as defined by Kroner and Sultan (1993).

$$\beta_t^{i/(\mathrm{BTCorGLD})} = \frac{h_t^{i/(\mathrm{BTCorGLD})}}{h_t^{(\mathrm{BTCorGLD})}} \tag{14}$$

To minimize the risk of a portfolio of two assets, a long position of \$1 taken in any given asset should be hedged by shorting $\beta_t^{i/(\mathrm{BTCorGLD})}$ dollars in the Bitcoin (or gold) market.

For a better analysis of the performance of the optimal portfolio, we calculate the Hedging Effectiveness index (HE) in Eq. (15), in alignment with Chang et al. (2011). This index evaluates the performance of the portfolio by comparing the variance of the hedged portfolio with that of the unhedged portfolio.

$$\mathrm{HE} = \frac{\mathrm{var}_{unhedged} - \mathrm{var}_{hedged}}{\mathrm{var}_{unhedged}} \tag{15}$$

where $\left(\mathrm{var}_{unhedged}\right)$ represents the variance of the unhedged portfolio returns (i.e., variance of the stock index or currency returns), and $\left(\mathrm{var}_{hedged}\right)$ denotes the variance of the hedged portfolio returns given in Eq. (16). A higher HE indicates a better risk reduction and a higher hedging effectiveness, which implies that the investment method can be considered as a superior hedging strategy.

$$\mathrm{var}\left(r_{h,t}|I_{t-1}\right) = \mathrm{var}\left(r_{j,t}|I_{t-1}\right) - 2\beta_{i,t}\,\mathrm{cov}\left(r_{j,t}, r_{i,t}|I_{t-1}\right) + \beta_{i,t}^2\,\mathrm{var}\left(r_{i,t}|I_{t-1}\right) \tag{16}$$

where $r_{h,t}$ is the hedged portfolio return; $r_{j,t}$ is the Bitcoin (or gold) return; $r_{i,t}$ is the stock index (or currency) return; and $\beta_{i,t}$ is the optimal hedge ratio calculated from Eq. (14).

3.4. Safe haven

The applied A-DCC model estimates the dynamic relationship between the different variables and the potential of Bitcoin and gold as a hedging asset over the total period. However, it does not specify the usefulness of Bitcoin and gold during crisis periods. Thus, this section assesses whether the Bitcoin and gold can serve as safe havens during the COVID-19 pandemic. Following Ratner and Chiu (2013) and Akhtaruzzaman, Boubaker, Lucey and Sensoy (2021), the econometric model to test the safe haven property is presented as follows:

$$ADCC_{ij,t} = \delta_0 + \delta_1 ADCC_{ij,t-1} + \delta_2 D_{\mathrm{covid}} + \vartheta_{ij,t} \tag{17}$$

where $ADCC_{ij,t}$ is the pairwise dynamic conditional correlation between Bitcoin (or gold) j and each return on a chosen asset i, and extracted from the estimated $\mathbf{Q}_t = \left\{q_{ij,t}\right\}_{i,j=1}^n$ in Eq. (7), such that,

$$ADCC_{ij,t} = \rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} \quad q_{jj,t}}}$$

We further create a dummy variable D_{covid} for the COVID-19 period, that equals one if the returns are during the crisis, and zero otherwise. According to Baur and McDermott (2010) and Bouri et al. (2017), if the constant δ_0 in Eq. (17) is weakly positive, then Bitcoin (or gold) is a weak diversifier against movements in the other asset i. Bitcoin (or gold) is a hedge against movements in the other asset if δ_0 is statistically not different from zero (weak hedge) or negative (strong hedge). Finally, Bitcoin (or gold) is a *weak* safe haven for the other asset during the crisis period if δ_2 is not significantly different from zero, or a *strong* safe haven if δ_2 is significantly negative.[2]

4. Data and descriptive statistics

4.1. Data

In the empirical part, we chose two major classes of financial assets, namely, stock indices and currencies. The data is collected from Thomson Reuters Datastream database. The daily closing prices of the main world stock markets correspond to the U.S. (Standard & Poor's 500, SP500), Eurozone (Euro STOXX 50, ES50), Japan (Nikkei 225, N225) and the U.K. (Financial Times Stock Exchange 100, F100). For currencies, we select the Euro (EUR), the Japanese yen (JPY) and the British pound (GBP). Bitcoin (BTC) prices are collected from www.coinmarketcap.com; and one ounce OR-LBMA of gold prices (GLD) are obtained from www.lbma.org.uk. All exchange rates are quoted against the U.S. dollar (USD). The sample spans the period from April 29, 2013 to January 5, 2021 with a total of 2007 observations.

The sample period encompasses a strong spread of the COVID-19 pandemic. Consequently, we divide the sample into two sub-periods to compare the behavior of Bitcoin and gold in terms of overall performance. The first period, from April 29, 2013 to March 10, 2020, before the crisis, and the second period from March 11, 2020 to January 5, 2021 during the crisis.[3] The empirical investigation is conducted on the returns computed as the logarithmic differences between prices $p_{i,t}$ for the asset i, such that $r_{i,t} = \ln p_{i,t} - \ln p_{i,t-1}$.

4.2. Preliminary analysis

Fig. 1 exhibits the evolution of daily prices for all asset classes. A dramatic price drop is observed from the second sub-period, especially for stock indices, indicating an increased variability during the pandemic. Indeed, the COVID-19 has led to a global recession and a huge liquidation in the financial markets (Aloui, Goutte, Guesmi, & Hchaichi, 2020). Moreover, Bitcoin lost more

[2] Note that Ratner and Chiu (2013) improved the method of Baur and McDermott (2010) to analyze the safe haven property of an asset by substituting the time varying coefficient b_t in the regression used by Baur and McDermott (2010) with the pairwise conditional correlation $ADCC_{ij,t}$.

[3] On March 11, 2020, the World Health Organization (WHO) has declared the COVID-19 disease as a global pandemic. Similar studies have used this date as the onset date of the crisis (Corbet, Larkin, & Lucey, 2020).

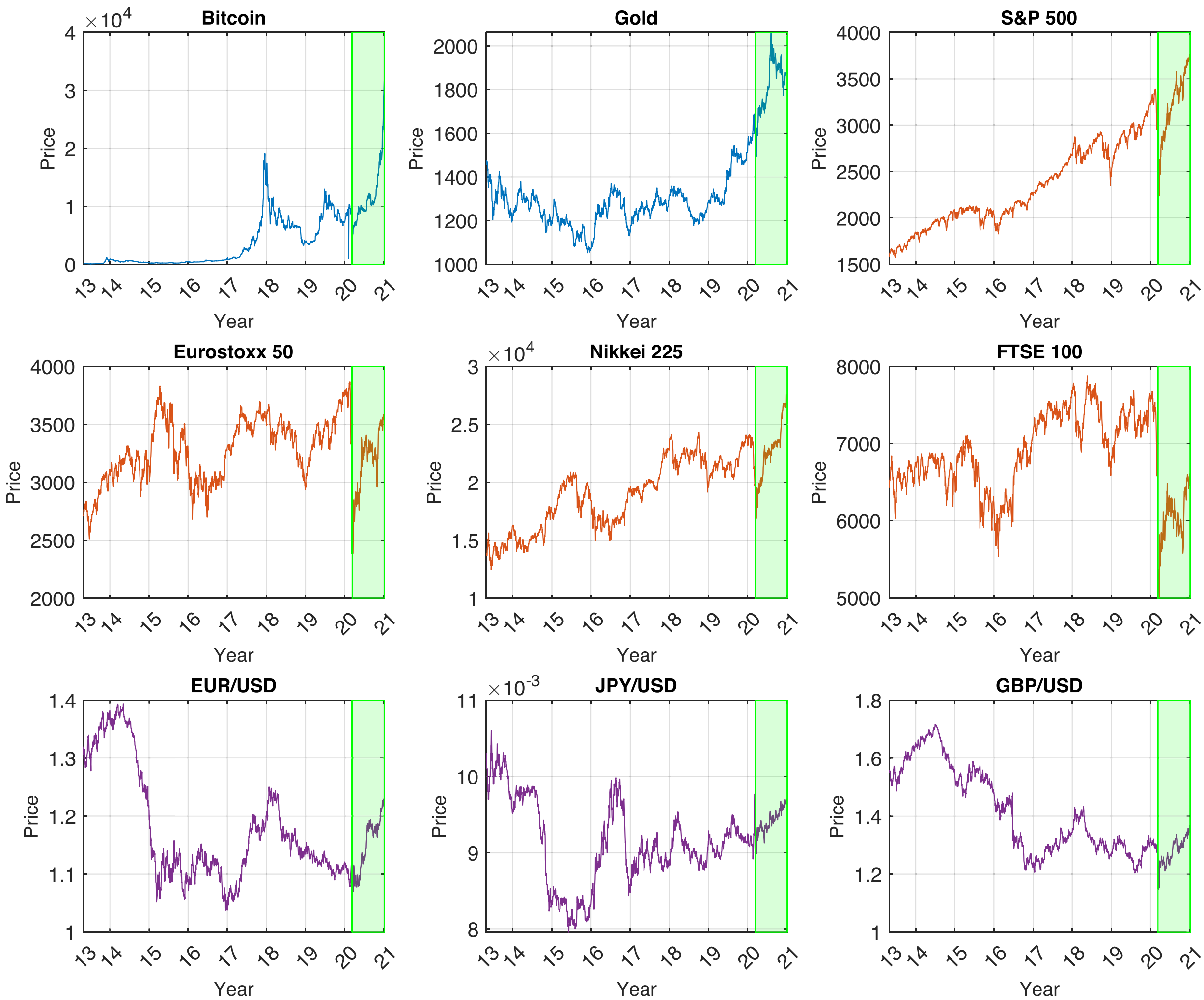

Fig. 1. Daily data for Bitcoin, gold, indices, and exchange rates. The shaded area corresponds to the COVID-19 pandemic period.

than half of its value, unlike gold which benefited from a much more homogeneous and stabilizing distribution. These qualitative results provide a first indication that Bitcoin investments can increase portfolio risk rather than acting as a safe haven. However, this drop was followed by a remarkable sharp rise for all assets. Bitcoin is undoubtedly the asset that has grown the most, after its first all-time high in December 2017, the price of Bitcoin explodes to new records with more than $32,000 on January 4, 2021.

Summary statistics of the returns are presented in Table 1. Going from the period preceding the crisis (Panel A) to the period following the announcement of the COVID-19 pandemic (Panel B), we notice that, with the exception of Bitcoin and two fiat currencies Euro and yen, gold and all other assets experienced an increase in their average returns accompanied with high volatility. Moreover, Bitcoin exhibits the highest return and highest risk during both sub-periods. As indicated by Baur et al. (2018), this spectacular growth is explained by a strong demand from institutional investors. For instance, Tesla announced on February 8, 2021 that it has bought $1.5 billion worth of Bitcoin, and it started accepting Bitcoin as a payment method for its products.[4] Furthermore, the Jarque–Bera test rejects normality for all data returns during both sub-periods.

The Ljung–Box test rejects the null hypothesis of absence of autocorrelation in the squared returns. Additionally, the ARCH test statistics for conditional heteroskedasticity are significant for all return series, which suggests the presence of ARCH effects. These results confirm our choice of GARCH-type models to analyze the dynamic relationship between Bitcoin (and gold) on one hand, and stock and foreign exchange (forex) markets on the other hand. Panels B presents the results of two unit root and stationarity tests, namely, the Augmented Dickey and Fuller (1979) (ADF) and Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS), which show that all series are stationary.

The Pearson correlations during both sub-periods are presented in Table 2. The correlations between Bitcoin (and gold) with the returns of other markets are negative and close to zero during the pre-COVID-19 period, which suggests that Bitcoin and gold can be used as hedging assets during the stable period (Baur & Lucey, 2010). During the second sub-period, with the exception of BTC/JPY pair, the correlations between Bitcoin (and gold) and other financial assets have become positive, signaling that the global financial markets became more interconnected. Thus, Bitcoin and gold might not have any safe haven property, yet they may offer some hedging characteristic. To test this assertion, we conduct more advanced empirical models in the following sections.

[4] Nevertheless, on May 12, 2021, Tesla stopped accepting Bitcoin as a payment method for its products. As a result, Bitcoin price plunged from a nearly $58,000 to below $38,000 in just 10 days.

Table 1
Summary statistics and unit root tests for daily returns.

	BTC	GLD	SP500	ES50	N225	F100	EUR	JPY	GBP
					Panel A: Before the COVID-19 pandemic				
Descriptive statistics									
Mean	0.0022	0.0001	0.0003	0.0000	0.0002	−0.0000	−0.0001	−0.0000	−0.0001
Std. dev.	0.0910	0.0083	0.0086	0.0109	0.0127	0.0086	0.0049	0.0056	0.0056
Skewness	0.1637	0.0693	−0.8002	−0.8587	−0.4860	−0.7607	0.0771	0.2674	−1.6691
Kurtosis	445.28	5.5613	11.196	9.6055	8.33187	9.3755	5.4598	7.4248	30.382
J-B test	8900.0†	498.02†	5203.7†	3476.2†	2181.5†	3206.1†	322.47†	935.09†	58009†
$Q^2(10)$	445.60[c]	196.58[c]	1050.9***	206.46***	202.96***	349.70***	169.55***	139.71***	85.980***
ARCH(10)	799.19***	130.92***	594.24***	140.97***	105.92***	255.12***	109.51***	104.12***	71.732***
Unit root test statistics									
ADF	−10.605***	−12.202***	−11.670***	−12.243***	−12.625***	−11.595***	−12.630***	−11.470***	−12.190***
KPSS	0.0799	0.3516	0.0872	0.1337	0.0929	0.1513	0.1279	0.1666	0.0737
					Panel B: During the COVID-19 pandemic				
Descriptive statistics									
Mean	0.0068	0.0007	0.0012	0.0009	0.0015	0.0005	0.0004	0.0001	0.0002
Std. dev.	0.0498	0.0124	0.0216	0.0203	0.0161	0.0185	0.0047	0.0051	0.0071
Skewness	−3.6822	−0.0001	−0.9150	−1.0657	0.3498	−0.8713	−0.5058	−1.4630	−0.6630
Kurtosis	40.045	8.7132	13.009	12.792	7.6616	11.435	4.7595	13.256	7.2672
J-B test	12606†	287.22†	1021.9†	885.68†	206.21†	665.97†	39.226†	1065.6†	199.85†
$Q^2(10)$	55.889**	28.251***	169.10***	44.717***	148.68***	52.724***	70.006***	63.381***	79.549***
ARCH(10)	5.0270*	2.3238*	91.517***	31.791***	86.170***	62.614***	28.269***	31.825***	48.156***
Unit root test statistics									
ADF	−5.9548***	−9.0835***	−9.0401***	−8.1735***	−8.4121***	−8.1858***	−9.2608***	−9.8608***	−7.8933***
KPSS	0.3888	0.0541	0.0342	0.0342	0.035	0.0533	0.1117	0.1296	0.0531

Note: This table reports the summary statistics of daily returns for different assets. J-B is the Jarque–Berra test for normality, $Q^2(10)$ is the Ljung–Box statistic for serial correlation in the squared returns. ARCH(10) is the test for conditional heteroskedasticity. ADF and KPSS stand for the empirical statistics of Augmented Dickey–Fuller and Kwiakowski–Phillips–Shmidt–Shin tests for unit root and stationarity, respectively. Panel A summarizes the results during the pre-COVID-19 period, i.e., from April 29, 2013 to March 10, 2020. Panel B summarizes the results during the COVID-19 pandemic, i.e., from March 11, 2020 to January 5, 2021.

† Normality is rejected at 5% significance level.
*** Null hypothesis is rejected at 1% confidence level.
** Null hypothesis is rejected at 5% confidence level.
* Null hypothesis is rejected at 10% confidence level.

Table 2
Pearson correlation matrix.

	BTC	GLD	SP500	ES50	N225	F100	EUR	JPY	GBP
					Panel A: Before the COVID-19 pandemic				
BTC	1	0.0069	0.0280	0.0075	−0.0112	0.0091	0.0047	−0.0007	0.0114
GLD		1	−0.0406	−0.0923	−0.1767	−0.0923	0.1915	0.0001	0.0661
SP500			1	0.1983	0.5560	0.5359	−0.0887	0.0050	0.0625
ES50				1	0.3004	0.8246	−0.2226	0.0038	0.1067
N225					1	0.2974	−0.1163	−0.0494	0.0305
F100						1	0.0019	0.0019	−0.0584
EUR							1	0.4522	0.5161
JPY								1	0.1611
GBP									1
					Panel B: During the COVID-19 pandemic				
BTC	1	0.1099	0.4604	0.4283	0.0787	0.4111	0.0845	−0.0724	0.1832
GLD		1	0.2209	0.1626	0.3026	0.1881	0.1735	0.0942	0.1854
SP500			1	0.6833	0.2435	0.6741	0.1389	−0.2857	−0.2208
ES50				1	0.4513	0.9124	0.1389	−0.2208	0.3187
N225					1	0.4167	0.2355	0.0489	0.3036
F100						1	0.1369	−0.1815	0.2250
EUR							1	0.5159	0.6089
JPY								1	0.4547
GBP									1

Note: This table reports the Pearson correlation matrix.

5. Empirical results

5.1. The A-DCC model estimation results

Tables A.1–A.3 in Appendix A document the full estimation results of the A-DCC model of Bitcoin and gold with all the returns of the selected assets before and during the COVID-19 pandemic. The average conditional correlations are weakly positive indicating the ability of Bitcoin and gold to act as a hedge in times of market stability and also in times of crisis.

Diagnostic tests on the residuals are performed to verify the quality of the empirical results. According to Table 3, Ljung–Box's test shows no serial correlation in the squared residuals. Likewise, the ARCH test cannot reject the null hypothesis of the absence of ARCH effects. Therefore, there is no evidence of erroneous statistical specification. The A-DCC approach with a TARCH specification is correctly specified to describe the dynamic relation-

Table 3
Diagnostic tests.

	BTC	GLD	SP500	ES50	N225	F100	EUR	JPY	GBP
					Panel A: Before the COVID-19 pandemic				
$Q^2(10)$	0.013 [1.000]	10.72 [0.380]	11.23 [0.340]	9.081 [0.524]	6.329 [0.787]	10.18 [0.425]	6.613 [0.761]	10.36 [0.409]	6.606 [0.762]
$Q^2(20)$	0.028 [1.000]	16.25 [0.700]	15.99 [0.719]	14.08 [0.826]	16.88 [0.663]	24.93 [0.204]	14.31 [0.814]	17.88 [0.595]	10.87 [0.949]
ARCH(10)	0.013 [1.000]	10.46 [0.401]	11.08 [0.351]	9.302 [0.504]	6.246 [0.794]	9.963 [0.444]	6.922 [0.733]	10.80 [0.373]	6.711 [0.752]
					Panel B: During the COVID-19 pandemic				
$Q^2(10)$	0.013 [1.000]	3.790 [0.956]	2.458 [0.992]	2.839 [0.985]	8.833 [0.548]	5.164 [0.880]	9.228 [0.511]	3.658 [0.962]	3.192 [0.977]
$Q^2(20)$	0.028 [1.000]	6.318 [0.998]	4.958 [1.000]	3.839 [1.000]	13.61 [0.850]	6.001 [0.999]	16.10 [0.710]	4.342 [1.000]	7.540 [0.995]
ARCH(10)	0.013 [1.000]	5.117 [0.883]	4.233 [0.936]	2.640 [0.989]	11.88 [0.293]	6.692 [0.754]	11.14 [0.346]	6.522 [0.770]	6.172 [0.801]

Note: This table reports the diagnostic tests for model misspecification: Ljung–Box $Q^2(10)$ and $Q^2(20)$, and the ARCH test on the residuals of the estimated A-DCC model. p-values associated with the statistical tests are reported in brackets. Lower p-values cast doubt on the correct specification of the model.

ship between Bitcoin and gold markets with the stock and forex markets.

Figs. 2 and 3 illustrate in detail the dynamics of the conditional correlations between Bitcoin and gold returns, respectively, and the various financial markets. Correlation levels are very volatile throughout the periods and markets. For stock indices, the results show that the A-DCC model alternates between low positive and negative values in alignment with Joy (2011), Klein (2017), Bouri, Shahzad, Roubaud, Kristoufek, and Lucey (2020) and Charfeddine, Benlagha, and Maouchi (2020), which indicate the role of Bitcoin and gold in hedging against stock markets. However, since the start of the pandemic outbreak, these correlations have increased on average. This can be attributed to two effects. (i) First, the collapse of stock markets, which were simultaneously affected by COVID-19. Indeed, the health crisis has turned into a serious economic crisis that has hit the markets more deeply than any other shock (Baker et al., 2020). Some shocks were due to the direct effects linked to the spread of the virus, i.e., infection rate, mortality rate, as well as the economic and psychological consequences due to social distancing and lockdown measures at various parts of the world, which has led to a massive sell-off in the financial markets. Some other shocks (whether positive or negative) were due to the direct implication of central bank monetary policy interventions (FOMC meetings, ECB, BOE, CBJ decisions) at various parts of the financial world and with different timing. (ii) Second, the sharp rise in the prices of Bitcoin and gold due to the crisis episodes prompted international investors to choose an optimal allocation strategy by investing in these assets to protect their wealth (Bofinger et al., 2020).

Goodell and Goutte (2021) suggest that Bitcoin may act as a safe haven during the pandemic due to its co-movement with COVID-19 cases. This explains that when the feeling of fear increases in the U.S. market, investors turn to other assets such as cryptocurrencies. However, the decrease in correlation appears to be only temporary and of short duration. Indeed, following government interventions with monetary and budgetary relief plans to mitigate the impact of the crisis, the correlations have shown episodes of positive values in Fig. 2, in alignment with Batten, Kinateder, Szilagyi, and Wagner (2021). For example, on March 17, 2020, the U.S. House passed the Coronavirus Aid, Relief, and Economic Security (CARES) act for an economic stimulus package exceeding $2 trillion to protect the American citizens from the unwanted health and economic impacts of COVID-19.

These results are of particular interest to investors who wish to hedge their portfolios. The following sections provide precise information on the hedge and safe haven properties.

5.2. Optimal portfolio design

Table 4 summarizes the optimal design of portfolios consisting of Bitcoin (or gold) and other financial assets before and during the COVID-19 crisis. The results indicate that, to minimize risk given the expected return, the optimal weights are generally above 92% for Bitcoin and 60% for gold during both sub-periods, on average. Mokni, Ajmi, Bouri, and Vo (2020) found similar results where investors hold more than 80% of their wealth in Bitcoin to minimize the risk of a U.S. equity portfolio. Likewise, this conclusion is similar to the works of Hood and Malik (2013), Arouri, Lahiani, and Nguyen (2015) and Chkili (2016) that reveal the usefulness of gold in providing downside risk hedging in international portfolios.

It is worth noting that during the crisis, the optimal weights of Bitcoin and gold in conventional currency wallets increased significantly, suggesting that forex investors are considering cryptocurrency and gold like a hedge (Longstaff, 2004). Moreover, during the COVID-19 pandemic, the optimal weights of Bitcoin and gold decreased for all stock market indices. The decrease is more pronounced with gold. For instance, the weight of the gold – S&P 500 portfolio decreased from 74.52% during the first phase to 19.31% during the second phase. Overall, the results conclude that investors should allocate larger proportions of Bitcoin than gold in order to minimize the risk of international wallets.

5.3. Hedging effectiveness

Optimal hedge weights and ratios provide a general understanding of how hedge is constructed to minimize risk. However, they do not help identify the effectiveness of the hedge over time. Therefore, we calculate the hedge effectiveness (HE) index using Eq. (15) in Table 5.

The comparison between portfolios including Bitcoin and those including gold varies considerably depending on the period and market type. Moving from Panel A (before COVID-19) to Panel B (during COVID-19) in Table 5, with the exception of the gold-currency pairs and the Bitcoin-Nikkei 225 pair that show a good hedging strategy, the optimal hedge ratios for Bitcoin and gold increased significantly during the crisis. In fact, for BTC-SP500 market, the ratio goes from a negative value of −0.0117 during the pre-COVID-19 period to a positive value of 0.2006 during the COVID-19 period. The negative value of HR implies that investors must take the same position for two assets in the same portfolio (short or long), while the positive value indicates reverse positions are required to hedge against the risk of each asset. For example, in order to minimize the risk, a long position of $1 in S&P 500 can be hedged with 20.06 cents short position in Bitcoin. As noted by López Cabrera and Schulz (2016), the lower the hedge ratio, the less expensive the hedge. Thus, asset coverage was cheaper before the pandemic than during the pandemic (Akhtaruzzaman, Boubaker, Lucey, & Sensoy, 2021). This finding is consistent with the literature which reveals higher hedge ratios in times of crisis (Batten et al., 2021), due to the sharp increase in uncertainty over the economic and financial outlook. The variety of risks associated with this global

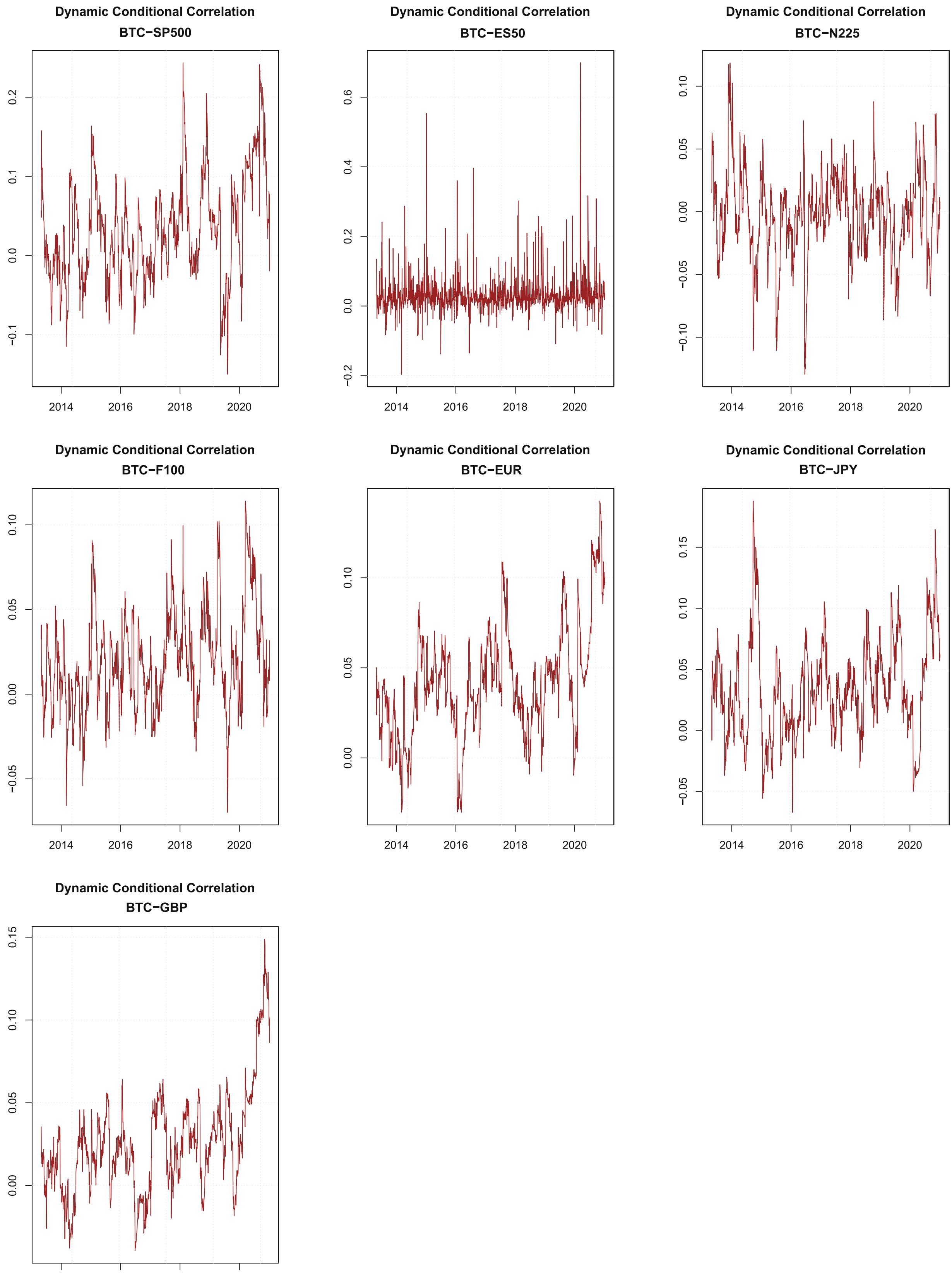

Fig. 2. Dynamic correlations between Bitcoin, stock indices and foreign exchanges.

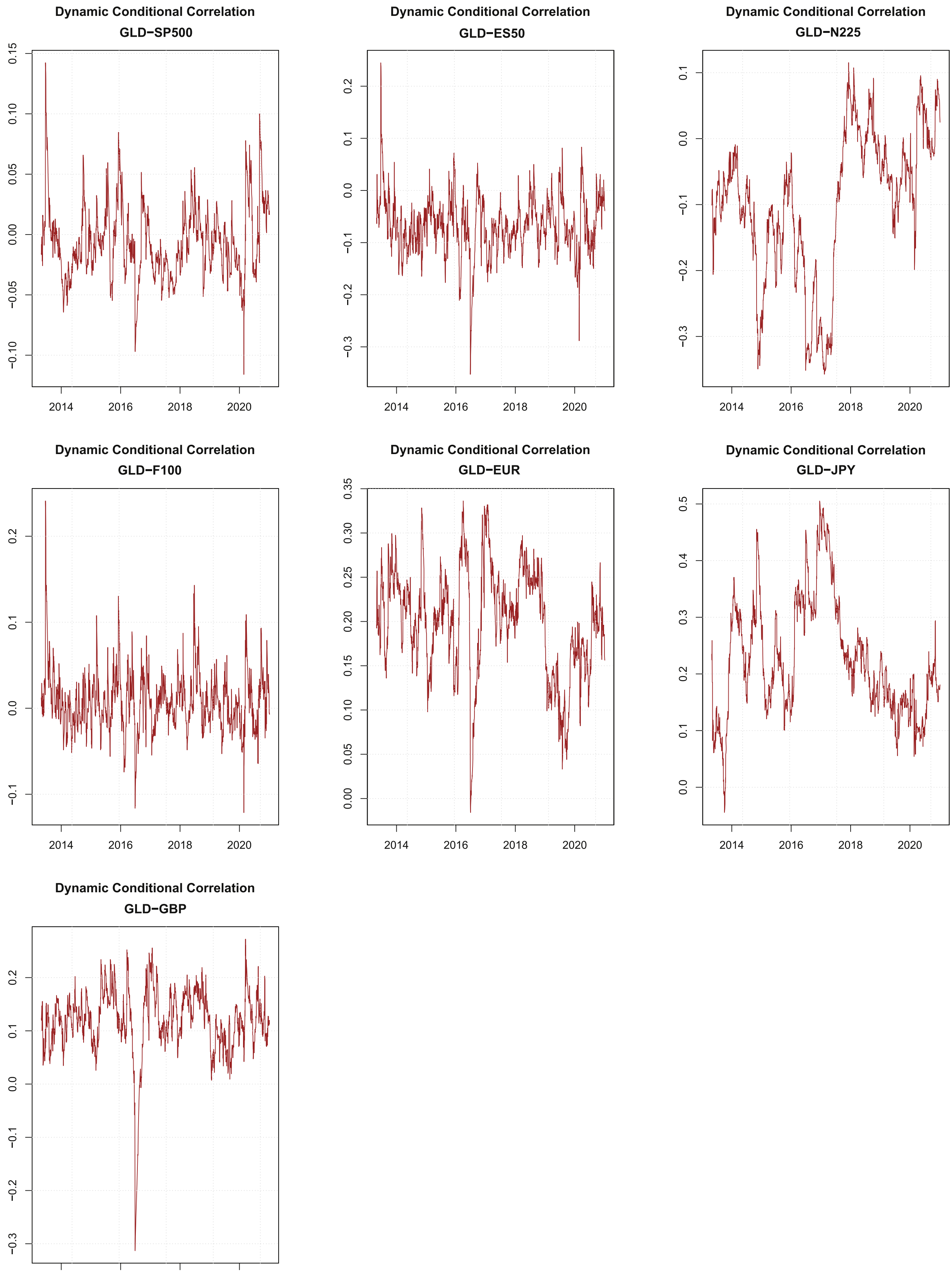

Fig. 3. Dynamic correlations between gold, stock indices and foreign exchanges.

Table 4
Optimal portfolio weights.

	BTC					GLD				
	Mean	Median	SD.	Min.	Max.	Mean	Median	SD.	Min.	Max.
Panel A: Before the COVID-19 pandemic										
SP500	0.9752	0.9813	0.0195	0.8830	0.9957	0.7452	0.7764	0.1257	0.3097	1
ES50	0.9704	0.9793	0.0293	0.7990	1	0.6167	0.6484	0.1733	0.0303	1
N225	0.9883	0.9516	0.0693	0.6800	1	0.3455	0.3434	0.1274	0.0998	0.6196
F100	0.9815	0.9876	0.0148	0.9260	1	0.7352	0.7554	0.1144	0.3467	0.9553
EUR	0.9939	0.9978	0.0095	0.9109	1	0.7842	0.8032	0.1288	0.3206	0.9956
JPY	0.9914	0.9933	0.0136	0.8870	1	0.7388	0.7566	0.1181	0.3173	0.9487
GBP	0.9900	0.9955	0.0150	0.8833	1	0.7123	0.7112	0.1208	0.3861	0.9459
Panel B: During the COVID-19 pandemic										
SP500	0.8265	0.8397	0.1433	0.1539	1	0.1931	0.1345	0.1482	0.0052	0.6875
ES50	0.5218	0.5054	0.2258	0	0.9558	0.0343	0.0290	0.0294	0	0.2131
N225	0.7283	0.7196	0.1141	0.2823	0.9465	0.2520	0.2669	0.1400	0	0.6754
F100	0.9114	0.9134	0.0642	0.6519	0.9653	0.3604	0.3554	0.1678	0.0184	0.7738
EUR	0.9952	0.9984	0.0082	0.9242	1	0.9118	0.9241	0.0579	0.6139	0.9933
JPY	0.9980	1	0.0860	0.9240	1	0.8830	0.9106	0.0913	0.3474	0.9832
GBP	0.9998	1	0.0015	0.9775	1	0.8109	0.8269	0.0981	0.4138	0.9804

Note: This table reports the optimal portfolio weights as in Eq. (13).

Table 5
Optimal hedge ratios (HR) and hedging effectiveness (HE) indices.

	BTC				GLD			
	HR	Var. HR	HE (%)	Var. unhedge	HR	Var. HR	HE (%)	Var. unhedge
Panel A: Before the COVID-19 pandemic								
SP500	−0.0117	0.4967	1.2070	0.5028	0.0215	0.4926	0.9191	0.5028
ES50	−0.0046	1.0006	0.7143	1.0096	0.0597	0.9694	2.2580	1.0096
N225	0.0202	3.2156	1.6592	3.2597	−0.1397	3.2333	0.8109	3.2597
F100	−0.0028	0.5828	0.2401	0.5843	0.0948	0.5667	2.5404	0.5843
EUR	0.0020	0.2416	0.0705	0.2418	0.1243	0.2299	4.6010	0.2418
JPY	0.0019	0.3219	0.0990	0.3222	0.1697	0.2942	6.8784	0.3222
GBP	0.0005	0.3011	0.0035	0.3011	0.0731	0.2945	1.7830	0.3011
Panel B: During the COVID-19 pandemic								
SP500	0.2006	6.3629	12.489	7.2206	0.3500	7.0340	2.9237	7.2206
ES50	0.5105	25.048	17.985	44.668	0.8122	43.031	3.6666	44.669
N225	−0.1090	6.5883	4.9090	6.8613	−0.1069	6.6842	2.9720	6.8613
F100	0.0674	2.8133	5.6992	3.0594	0.1926	2.9754	1.7943	3.0594
EUR	0.0217	0.1968	4.5066	0.2061	0.0592	0.2011	2.4390	0.2061
JPY	0.0291	0.2585	7.3541	0.2762	0.0645	0.2699	2.3035	0.2762
GBP	0.0530	0.3877	12.854	0.4449	0.0865	0.4337	2.5367	0.4449

Note: This table reports the optimal hedge ratios (HR) from Eq. (14), and hedging effectiveness (HE) indices from Eq. (15).

spread of the virus has affected the whole world regardless of the level of economic development of the country. International stock and forex markets have experienced intense volatility. Higher market and credit risks have increased hedging costs for international investors.

Regarding the hedging efficiency, a higher HE index indicates better risk reduction and greater hedging efficiency. Before the COVID-19 pandemic, with the exception of the S&P 500 and Nikkei 225 stock indices, the estimated HE for gold is greater than Bitcoin but with low risk reduction, which can only reach 6.87%. for the GLD-JPY case. The results are consistent with Shahzad, Bouri, Roubaud, and Kristoufek (2020) where the effectiveness of hedging with gold is better than with Bitcoin for several stock indices. Likewise, Charfeddine et al. (2020) reveal that, compared to gold, cryptocurrencies are not effective hedging instruments in most of the considered cases. Besides, during the health crisis, the effectiveness values of the portfolio hedging are higher with Bitcoin than with gold, which shows that cryptocurrency seems to be a better and more efficient hedging tool than gold in times of turbulence. Our results offer interesting information for portfolio design and are useful for investors and financial advisers looking for the best asset among Bitcoin and gold to hedge extreme movements in stock indices and exchange rates.

Even if Bitcoin seems to be a more effective hedging tool than gold in times of turbulence, it should be noted that, whatever the period considered, the hedging capacity of these two assets remains, for most cases, very low (Corbet et al., 2018; Guesmi et al., 2019; Klein et al., 2018). Our results have important implications. Hedge ratios vary considerably during the sampling period, implying that the covered positions need to be updated regularly. Hence, for international investors who intend to diversify their portfolios and support their wealth, ignoring any significant market variation can lead to wrong decisions. Furthermore, the confidence of investors and portfolio managers in the precious metal needs to be reassessed during the recent crisis, regardless of the idea that gold performs better under such circumstances (Baur & McDermott, 2010). The ability of Bitcoin to outperform gold and absorb small shocks is mainly due to the low dependence between digital assets and conventional assets. Therefore, even though the cryptocurrency markets represent a tiny proportion of the financial markets, it is only a matter of time before they become the mainstream. Additionally, cryptocurrencies are still much riskier than precious metals and other assets, having a high Bitcoin weight could lead to excessive volatility of portfolio returns. Consequently, any change in this asset class requires careful monitoring. Policymakers, risk managers and international investors should be aware of the potential risks, arising from cryptocurrencies, which could desta-

Table 6
Safe haven property of Bitcoin and gold.

	SP500	ES50	N225	F100	EUR	JPY	GBP
				BTC			
δ_0	0.0007* (0.0003)	0.0010* (0.0004)	0.0011* (0.0004)	0.0011* (0.0005)	0.0025 (0.0014)	0.0024 (0.0012)	0.0024* (0.0011)
δ_1	0.9623*** (0.0061)	0.9465*** (0.0073)	0.9280*** (0.0084)	0.9465*** (0.0072)	0.9432*** (0.0076)	0.9405*** (0.0077)	0.9362*** (0.0080)
δ_2	0.0036** (0.0013)	0.0046** (0.0014)	0.0083*** (0.0017)	0.0050** (0.0017)	0.0172*** (0.0052)	0.0183*** (0.0045)	0.0140*** (0.0039)
				GLD			
δ_0	0.0225* (0.0111)	0.0250* (0.0104)	0.0224* (0.0091)	0.0293* (0.0122)	0.0701 (0.0362)	0.0611* (0.0290)	0.0558* (0.0242)
δ_1	0.9262*** (0.0084)	0.9104*** (0.0092)	0.9008*** (0.0097)	0.9063*** (0.0094)	0.8973*** (0.0098)	0.9019*** (0.0096)	0.8966*** (0.0099)
δ_2	0.0337 (0.0331)	0.0364 (0.0312)	0.0623* (0.0278)	0.0426 (0.0363)	0.2012 (0.1107)	0.1661 (0.0885)	0.1375 (0.0736)

Note: This table reports the estimation results of the safe haven model in Eq. (17). Standard deviations are in parentheses.
*** Statistically different from zero at 1% confidence level.
** Statistically different from zero at 5% confidence level.
* Statistically different from zero at 10% confidence level.

bilize financial markets and affect the health of the economy as a whole.

5.4. Safe haven property

In this section, we focus on the safe haven property during extreme movements of the health crisis. Table 6 displays the estimated coefficients of the model in Eq. (17).

For Bitcoin, all assets have significantly positive δ_2 coefficient, which indicates that this cryptocurrency cannot be considered as a solid safe haven for these assets during the COVID-19 period. The result is consistent with Conlon and McGee (2020) and Ji, Zhang, and Zhao (2020) who find that the safe haven role becomes less effective for Bitcoin and most altcoins during the COVID-19 pandemic. Likewise, Ghorbel and Jeribi (2021) reveal that none of the cryptocurrencies can serve as a safe haven during the global pandemic of 2020, and Dutta, Das, Jana, and Vo (2020) found that Bitcoin can only act as a diversifier for oil during COVID-19. Indeed, investing in Bitcoin appears to be a high risk strategy and could not be a safe haven during COVID-19. Its losses exceeded those of currencies and stock markets.

For gold, the coefficient δ_2 is positive, yet statistically not different from zero for all assets, except for the Nikkei 225. This proves that gold's traditional safe haven property is maintained in its weak form during the recent pandemic. Indeed, despite the gradual reopening of the global economies, the relief plans introduced by various governments against the global recession, and the advances in different types of the COVID-19 vaccines, financial market investors remain reluctant and exhibit massive fear due the apparition of more dangerous variants of the virus SARS-CoV-2. Our results reinforce the findings of Dutta et al. (2020), Ji et al. (2020), Akhtaruzzaman, Boubaker, Lucey and Sensoy (2021) and Salisu, Raheem, and Vo (2021) that support the safe haven property of gold against the downside risk of portfolios during the pandemic.

6. Conclusion

The COVID-19 health crisis has severely shaken the financial markets around the world. Investors confidence in the financial institutions has been disrupted, thus, prompting the need to explore other investment avenues capable of resisting this situation. Our study compares Bitcoin and gold hedging and safe haven properties against stock and foreign exchange markets of several developed countries.

The empirical application is conducted on four main world stock indices, mainly, S&P 500, Euro Stoxx 50, Nikkei 225, FTSE 100; and three major currencies quoted against the U.S. dollar, mainly, Euro, JPY, and GBP. The sample spans the period from April 29, 2013 to January 5, 2021. Based on the multivariate asymmetric dynamic conditional correlation (A-DCC) model, the hedge ratios and the hedge effectiveness indices show the ability of Bitcoin and gold to act as hedges in times of market stability and also in times of stress. Moreover, the analysis provides evidence that during the COVID-19 pandemic, gold maintains its role as a (weak) safe haven for the considered assets, except for Nikkei 225. Bitcoin, on the other hand, cannot provide shelter during the pandemic due to its increased variability.

While the results provide relevant information for governments, regulators and investors to avoid losses in times of high uncertainty, they should not be taken for granted. Indeed, it is not possible to draw any concrete conclusions at this stage. While the global financial markets are still reeling from COVID-19, we may have to wait some time until the final picture emerges.

Future research could implement the Value-at-Risk (VaR) analysis in a time rolling-window manner to detect and manage market risks over different time horizons, and investigate portfolio profit & loss (P&L) dynamics. The curious researcher could expand the analysis to include other digital assets to examine their diversification potential and to find out if they can outperform Bitcoin and gold and can offer better hedge. Scholars could inquire how government stimulus packages play a role in mitigating the effects of COVID-19 and their impacts on portfolio optimization.

Additional studies may address questions regarding hedging strategies and risk diversification through commodities and digital assets versus stocks at the sector level, since various sectors are heterogeneous and have different market structures. This can provide comprehensive information to portfolio managers in order to make sound portfolio allocation decisions.

Appendix A. Full estimation results

Table A.1

Table A.1
TARCH model estimation results.

	BTC	GLD	SP500	ES50	N225	F100	EUR	JPY	GBP
					Panel A: Before the COVID-19 pandemic				
c	0.1528***	0.0023	0.0519***	0.0308	0.0549***	0.0094	−0.0140	−0.0140	−0.0120
	(0.0345)	(0.0155)	(0.0117)	(0.0191)	(0.0166)	(0.0128)	(0.0095)	(0.0093)	(0.0105)
ϕ_1	−0.0170	0.0296	−0.0380	−0.0150	−0.0010	0.0329***	0.0029	0.0011	0.0172
	(0.0205)	(0.0214)	(0.0227)	(0.0249)	(0.0195)	(0.0094)	(0.0247)	(0.0233)	(0.0296)
ω	0.2913*	0.0148**	0.0392***	0.0451***	0.0634***	0.0450***	0.0014	0.0068**	0.0040***
	(0.1730)	(0.0072)	(0.0074)	(0.0138)	(0.0154)	(0.0127)	(0.0010)	(0.0130)	(0.0014)
α_1	0.4085	0.0631***	0.1444***	0.1072***	0.1254***	0.1020***	0.0393***	0.0789***	0.0391***
	(0.2653)	(0.0144)	(0.0143)	(0.0170)	(0.0197)	(0.0177)	(0.0047)	(0.0130)	(0.0041)
β_1	0.8020***	0.9345***	0.8417***	0.8759***	0.8592***	0.8668***	0.9676***	0.9308***	0.9638***
	(0.0365)	(0.0172)	(0.0166)	(0.0242)	(0.0223)	(0.0254)	(0.0015)	(0.0128)	(0.0008)
γ_1	−0.0310	−0.1175	1.0000***	1.0000***	0.9999***	1.0000***	0.2406*	−0.1600	0.3980**
	(0.0641)	(0.1214)	(0.1171)	(0.1201)	(0.1474)	(0.1593)	(0.1368)	(0.1133)	(0.1522)
ν_i	2.2375***	6.8389***	5.6213***	5.3498***	4.0380***	6.3548***	6.5963***	4.6947***	5.3554*
	(0.3696)	(0.9648)	(1.5995)	(1.7727)	(0.6122)	(1.5980)	(2.0676)	(0.8289)	(3.1634)
					Panel B: During the COVID-19 pandemic				
c	0.5015***	0.0928	0.2081***	0.0491	0.0667	0.0353	0.0678**	0.0308	0.0240
	(0.1653)	(0.0789)	(0.0550)	(0.0717)	(0.0675)	(0.0569)	(0.0279)	(0.0219)	(0.0447)
ϕ_1	−0.1750***	0.0548	−0.2330***	−0.0560	−0.0840	−0.1080***	0.0821*	−0.0920	0.0706
	(0.0584)	(0.0214)	(0.0649)	(0.0503)	(0.0759)	(0.0276)	(0.0482)	(0.1062)	(0.0607)
ω	0.0730*	0.0810	0.0530	0 (0.1	0.0249	0.0134	0.0626*	0.2758	0.0710**
	(0.0628)	(1.6418)	(0.0388)	(0.1479)	(0.0304)	(0.0211)	(0.0336)	(0.2580)	(0.0305)
α_1	0.0781**	0.1270	0.1857***	0.0845***	0.1430*	0.0763*	0.2157***	0.4312*	0.0940*
	(0.0320)	(0.2182)	(0.0719)	(0.1853)	(0.0836)	(0.0343)	(0.0834)	(0.2429)	(0.0590)
β_1	0.9406***	0.4331	0.8314***	0.9412***	0.8814***	0.9349***	0.6843***	0.1797	0.8156***
	(0.0174)	(1.5020)	(0.0573)	(0.2124)	(0.0680)	(0.0308)	(0.1070)	(0.5339)	(0.0745)
γ_1	−0.5470	0.9999	0.1578	1 (2.5	0.4907*	0.8699*	−0.1990	−0.2350	0.9999
	(0.3951)	(0.7540)	(0.2524)	(2.5730)	(0.2596)	(0.4773)	(0.1893)	(0.2328)	(0.7646)
ν_i	2.5809***	3.9801***	3.6584***	3.5359***	4.7381***	4.8585***	96.0450	2.8836***	11.2690*
	(0.1214)	(1.0128)	(0.4861)	(0.6215)	(0.7460)	(1.2441)	(94.2904)	(1.0477)	(6.7924)

Note: This table reports the estimation results of the TARCH model in Eq. (5). Panel A reports the results for the sub-period from April 29, 2013 to March 10, 2020, before the COVID-19 pandemic. Panel B reports the results for the sub-period from March 11, 2020 to January 5, 2021, during the COVID-19 pandemic. Standard deviations of the estimated coefficients are in parentheses.

* Statistically significant at 10% confidence level.
** Statistically significant at 5% confidence level.
*** Statistically significant at 1% confidence level.

Table A.2

Table A.2
A-DCC model estimation results between Bitcoin, stock indices and foreign exchanges.

	SP500	ES50	N225	F100	EUR	JPY	GBP
				Panel A: Before the COVID-19 pandemic			
a	0.0138 (0.0212)	0.0086 (0.1464)	0.0180 (0.0113)	0.0101 (0.0157)	0.0000 (0.0010)	0.0000 (0.0166)	0.0000 (0.0079)
b	0.9623*** (0.2830)	0.9203 (1.6059)	0.9449*** (0.0982)	0.9336*** (0.1853)	0.9797*** (0.1207)	0.9318*** (0.0314)	0.9689*** (0.1345)
g	0.0000 (0.0977)	0.0000 (0.1140)	0.0000 (0.0364)	0.0000 (0.0255)	0.0000 (0.0014)	0.0270 (0.0277)	0.0000 (0.0043)
ν	4.0000* (2.1472)	4.0000 (3.8541)	4.0000*** (0.4290)	4.0000 (3.4246)	4.0000 (4.8778)	4.0000*** (0.7679)	4.0000 (13.5200)
Log(L)	−7120.1	−7690.5	−7915.9	−7311.3	−6414.9	−6568.9	−6608.2
AIC	7.9722	8.6092	8.8609	8.1857	7.1847	7.3566	7.4005
BIC	8.0304	8.6675	8.9192	8.2439	7.2429	7.4149	7.4588
				Panel B: During the COVID-19 pandemic			
a	0.0000 (0.0317)	0.0188 (0.0548)	0.0000 (0.0688)	0.0137 (0.0431)	0.0000 (0.0051)	0.0000 (0.0306)	0.0000 (0.0284)
b	0.9174*** (0.2342)	0.0327 (0.0315)	0.9213*** (0.1127)	0.0143 (0.0103)	0.9702*** (0.1900)	0.9648*** (0.0281)	0.9401*** (0.0648)
g	0.0000 (0.0319)	0.9443*** (0.1356)	0.0000 (0.0466)	0.0000*** (0.0951)	0.0000 (0.0090)	0.0477** (0.0227)	0.0000 (0.0218)
ν	4.0000*** (0.6864)	4.0000** (2.0396)	4.0000*** (0.8927)	4.0000*** (0.7846)	4.2518*** (0.5501)	4.0000* (1.7508)	4.0000 (0.5360)
Log(L)	−940.22	−967.07	−934.80	−959.66	−708.47	−668.62	−779.84
AIC	8.9647	9.2156	8.914	9.1464	6.7988	6.4263	7.4658
BIC	9.2635	9.5145	9.2129	9.4452	7.0977	6.7252	7.7646

Note: This table reports the estimation results of the asymmetric DCC model in Eq. (7) between Bitcoin and other assets. Panel A reports the results for the sub-period from April 29, 2013 to March 10, 2020, before the COVID-19 pandemic. Panel B reports the results for the sub-period from March 11, 2020 to January 5, 2021, during the COVID-19 pandemic. The degrees-of-freedom of the multivariate Student's t distribution is denoted ν. Standard deviations of the estimated coefficients are in parentheses. Log(L) is the log-likelihood value. AIC and BIC stand for the Akaike information criterion per observation, and Bayesian information criterion per observation, respectively.

* Statistically significant at 10% confidence level.
** Statistically significant at 5% confidence level.
*** Statistically significant at 1% confidence level.

Table A.3

Table A.3
A-DCC model estimation results between gold, stock indices and foreign exchanges.

	SP500	ES50	N225	F100	EUR	JPY	GBP
				Panel A: Before the COVID-19 pandemic			
a	0.0138 (0.0212)	0.0086 (0.1464)	0.0180 (0.0113)	0.0101 (0.0157)	0.0000 (0.0010)	0.0000 (0.0166)	0.0000 (0.0079)
b	0.9623*** (0.2830)	0.9203 (1.6059)	0.9449*** (0.0982)	0.9336*** (0.1853)	0.9797*** (0.1207)	0.9318*** (0.0314)	0.9689*** (0.1345)
g	0.0000 (0.0977)	0.0000 (0.1140)	0.0000 (0.0364)	0.0000 (0.0255)	0.0000 (0.0014)	0.0270 (0.0277)	0.0000 (0.0043)
ν	4.0000* (2.1472)	4.0000 (3.8541)	4.0000*** (0.4290)	4.0000 (3.4246)	4.0000 (4.8778)	4.0000*** (0.7679)	4.0000 (13.5200)
Log(L)	−3917.3	−4475.2	−4707.5	−4090.6	−3147.2	−3311.7	−3373.5
AIC	4.3957	5.0185	5.278	4.5892	3.5356	3.7193	3.7884
BIC	4.4539	5.0768	5.3363	4.6474	3.5939	3.7776	3.8467
				Panel B: During the COVID-19 pandemic			
a	0.0000 (0.0269)	0.0344 (0.0352)	0.0342 (0.0268)	0.0107 (0.0242)	0.0000 (0.0197)	0.0000** (0.0322)	0.0000 (0.0313)
b	0.9554*** (0.1168)	0.9379*** (0.1100)	0.8818 (0.6978)	0.9471*** (0.0472)	0.9372*** (0.0765)	0.9149*** (0.0926)	0.9235*** (0.1255)
g	0.0000 (0.0135)	0.0000 (0.1916)	0.0000 (0.2522)	0.0000 (0.0521)	0.0000 (0.0214)	0.0000 (0.0155)	0.0000 (0.0339)
ν	4.0046*** (0.4068)	4.0358*** (0.4921)	5.2773*** (1.1275)	4.6775*** (0.7682)	8.3907*** (2.2806)	4.0000*** (0.6393)	6.3377*** (1.3579)
Log(L)	−689.64	−724.28	−680.37	−716.13	−456.74	−430.09	−529.95
AIC	6.6228	6.9465	6.5361	6.8703	4.4462	4.1971	5.1304
BIC	6.9217	7.2454	6.835	7.1692	4.7451	4.496	5.4292

Note: This table reports the estimation results of the asymmetric DCC model in Eq. (7) between gold and other assets. Panel A reports the results for the sub-period from April 29, 2013 to March 10, 2020, before the COVID-19 pandemic. Panel B reports the results for the sub-period from March 11, 2020 to January 5, 2021, during the COVID-19 pandemic. The degrees-of-freedom of the multivariate Student's t distribution is denoted ν. Standard deviations of the estimated coefficients are in parentheses. Log(L) is the log-likelihood value. AIC and BIC stand for the Akaike information criterion per observation, and Bayesian information criterion per observation, respectively.

* Statistically significant at 10% confidence level.
** Statistically significant at 5% confidence level.
*** Statistically significant at 1% confidence level.

Declaration of competing interest

The authors report no declarations of interest.

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