COVID-19 and the volatility interlinkage between bitcoin and financial assets

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Abstract
We investigate the effects of COVID-19 on volatility connectedness between bitcoin and five traditional financial assets from the gold, oil, foreign exchange, stock, and bond markets, employing high-frequency data. The empirical analyses are carried out using the wavelet coherence approach and dynamic frequency-domain connectedness method. Our results generally indicate that the volatility dynamics between bitcoin and the financial assets are weak or negative before the pandemic while they become positive during the pandemic times for most of the assets. Further, the volatility connectedness for bitcoin-gold and bitcoin-foreign exchange pairs is most significant in the short term, while it is significant in the intermediate term for bitcoin-oil and bitcoin-equity pairs during the pandemic. We examine optimal portfolios to hedge Bitcoin shocks at multiple investment horizons during the pandemic. We find that most of these financial assets perform as a good hedger against Bitcoin shocks in the short and long term but not in the medium term.

Keywords COVID-19 · Wavelet coherence · Volatility interdependence · Bitcoin · Dynamic Frequency-domain connectedness

JEL classification Codes: C58 · G15 · C14 · G10

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1 Introduction

Bitcoin is the most well-known and popular digital currency with a market capitalization that exceeded 1,000 billion USD on May 11, 2021. It has been classified as two extremes. On the one hand, it can be regarded as a speculative asset due to its high price volatility (Cheah and Fry 2015; Yermack 2015). For example, its realized volatility is up to ten times higher than that of fiat currency markets (Baur and Dimpfl 2021). On the other hand, it can be regarded as a risk hedging tool due to its independence from monetary policy and weak correlation with traditional assets. For example, the statistical properties of bitcoin make it uncorrelated with stocks, bonds, and commodities in normal market conditions and in crises periods (Baur et al., 2018; Dyhrberg 2016; Bouri et al. (2017a, b), and Urquhart and Zhang (2018) articulate the hedging role performed by bitcoin against asset classes such as stocks and currencies. To assess the diversification capabilities of Bitcoin, we need to examine its volatility connectedness with other conventional assets during the COVID-19 pandemic. Bitcoin faced the first acute market crisis during the COVID-19 pandemic since the launch of its futures contracts in December 2017. Thus, in this paper, we assess the volatility interdependence between bitcoin and major asset classes (oil, foreign currency, gold, stocks, and bonds) during the pandemic, which is considered a “once-in-a-century” health crisis (Gates, 2020).

Since the coronavirus (COVID-19) was first diagnosed as a health pandemic in March 2020, it has spread to almost every country of the globe. The pandemic has caused significant disruption to the economy and an unparalleled slump in financial markets. For example, one day after the announcement, the indices of major developed stock markets, i.e., US (S&P500), UK (FTSE-100), and Japan (Nikkei-225) stock markets dropped by about 9.51%, 10.87%, and 4.41%, respectively. Bitcoin value decreased almost to half from 9000 USD to around 4000 USD between March 7 and March 13. The Brent crude oil price dropped to the lowest level (22.58 USD) since November 2002 by the end of March 2020. The spread of fear and anxiety by the pandemic created a decrease in market value and an increase in market volatility. This reduces diversification benefits given the high market volatility (Campbell et al., 2002).

The accompanying heightened level of risk during this unprecedented pandemic forces individuals and institutions to seek investments that are uncorrelated with other investment classes to hedge against financial risk. Accordingly, a growing number of studies has emerged to address the safe-haven properties of bitcoin during crises by examining how bitcoin returns relate to other traditional financial assets (e.g., Conlon and McGee, 2020; Kristoufek, 2020; Dutta et al., 2020; Ji et al. 2020; Goodell and Goutte, 2021; Caferra and Vidal-Tomás, 2021). However, the literature on volatility dynamics between bitcoin and other asset classes during the period surrounding the COVID-19 pandemic has so far been underexplored. Investors should be more concerned about asset return volatility during the pandemic because the utility from avoiding losses exceeds that from potential gains (Hwang and Satchell, 2010). Accordingly, in this study, we try to fill this gap by examining the volatility interdependence between bitcoin and important asset classes, including foreign currency, US equity,
oil, gold, and bonds in the period surrounding the COVID-19 pandemic, using high-frequency data.

Furthermore, few studies have examined the volatility interdependence between bitcoin and other asset classes in both time and frequency (over different time horizons). Observing dependence among asset classes at different investment horizons is vital for investors because their preference for risk is inversely related to time horizon, and thus, changing association across periods has critical direct implications for asset allocation (Marshall, 1994; Samuelson, 1989).1

We apply the cross-wavelet power transform, the cross-wavelet coherency, and the dynamic frequency-domain connectedness on daily realized volatility constructed from high frequency data (5-min). These methods can capture the linkages over time and different frequency domains. We find that bitcoin-gold and foreign currency were the greatest two pairs affected by the pandemic. They both witnessed connectedness peaks two times during the pandemic originating mainly from short-term horizon. In contrast, the volatility connectedness for bitcoin-oil and bitcoin-S&P 500 pairs comes mainly from the intermediate horizon. For the bitcoin-oil pair, the volatility changes from the short term in the early period (January to May 2020) to the intermediate term in the later period (during November 2020). Finally, the pandemic effect on volatility connectedness was the lowest for the bitcoin-bond pair.

The changing dynamic of risk transfer during the COVID-19 pandemic suggests that the hedge ratio and optimal portfolios are likely to differ over the sample period. Hence, we use conditional variance estimates (DCC-GARCH) to construct hedge ratios and optimal portfolio weights. We find that hedging bitcoin became more costly during the pandemic yet more effective when using gold, foreign currency, and S&P 500, particularly over the medium term. Gold, foreign currency, and bonds became less effective during the pandemic.

2 Literature review

This section presents a brief literature review of the studies investigating the interconnection between bitcoin and other asset classes during the COVID-19 pandemic. Conlon and McGee (2020) tested the downside risk of bitcoin during the COVID-19 pandemic finding that it raised risk relative to holding the S&P 500 alone. In contrast, by using the dynamic conditional correlation, Mariana et al., (2020) found that daily returns of bitcoin correlated negatively with S&P 500, indicating that it has safe-haven traits. Chen et al. (2020) showed that coronavirus created negative sentiment as measured by the search volume of coronavirus-related keywords. They used this sentiment as a measure of the fear index, which they show that it lowered bitcoin returns. Kristoufek (2020) claimed that gold is a better risk diversifier during the pandemic than bitcoin. Specifically, bitcoin correlation with S&P 500 returns increased markedly during the pandemic. His claim is based on the safe-haven definition from Baur and Lucey (2010); Beckmann et al. (2015); and Klein (2017) that the asset correlation with other assets during turbulent periods should be not higher than during regular

1 For more details, see Maghyereh and Abdoh (2020).
periods. Similarly, Dutta et al. (2020) compared the safe-haven property of bitcoin to gold against investment risks in the oil market during the pandemic using the DCC-GARCH model of Engle (2002). They find that portfolio risk is reduced significantly when including gold, rather than bitcoin, with oil. Bitcoin was found as a diversifier in their study since the pandemic strengthened the conditional correlation between it and oil.

Conlon et al. (2020) estimated the portfolio downside risk using value at risk (VAR) and its conditional version (CVAR) for a portfolio that combines bitcoin and one international equity market index including United States, United Kingdom, Italy, Spain, and China finding that the downside risk of the portfolio increased relative to holding only the equity market index. Caferra and Vidal-Tomas (2021) investigated the co-movement between Bitcoin and Ethereum, SP 500, and Euro Stoxx 50 during the pandemic using the Markov switching autoregressive model. They find co-movements between cryptocurrencies and stock markets during the main period of the panic.

Goodell and Goutte (2021) applied a large-scale analysis investigating the paired co-movement between six cryptocurrencies with fourteen equity indices and an index of market volatility (VIX) during the COVID-19 period. Using different econometric techniques, including wavelet coherence analysis, principal component analysis, and neural network analysis, they revealed that bitcoin comove positively with the VIX and thus support the safe-haven role of this cryptocurrency as it yields higher return during uncertain periods. They conclude that bitcoin is an effective safe-haven asset, especially during market turmoil. In contrast, Ji et al. (2020) utilized cross-quantilogram analysis for a mean–variance optimized portfolio containing equity indices and several asset classes, including bitcoin. Given their findings of the non-stability of tail-quantiles during the COVID-19 pandemic, they conclude that bitcoin is not an effective safe-haven asset. We note that the role of bitcoin as a safe haven is not a settled issue and is open for debate. It is role during the COVID-19 period is still developing. Goodell and Goutte (2021) revealed that bitcoin comove positively with the VIX and thus support the safe-haven role of this cryptocurrency as it yields higher returns during uncertain periods. While Smales (2019) does not find consistent evidence, over the periods 2011–2018, with this role as Bitcoin returns exhibits greater variability than other assets, we address how Bitcoin volatility comoves with the volatilities of traditional financial assets during the COVID-19 period. Again, the haven role of Bitcoin during this crisis is not settled.

The previous overview of the literature suggests that bitcoin’s role in diversification and risk hedging needs to be further examined. We bridge the gap and offer insights about volatility connectedness between bitcoin and financial assets during the pandemic.

### 3 Methodology

In this study, we are primarily interested in measuring the extent of the volatility interdependence between bitcoin and four asset classes. To achieve that, we employ three econometric methods, including Granger-causality network analysis, wavelet
coherence, and dynamic frequency-domain connectedness approach. The Granger-
causality network method proposed in Billio et al. (2012) allows us to identify the
direction of relationships and nodes between our variables.

To characterize the relation between bitcoin and other asset classes in time and
frequency fashion (i.e., the short-term, medium-term, and long-term), we apply the
wavelet coherence method of Torrence and Compo (1998). This methodology allows
us to assess the relation in every point of our sample period across different time
horizons. This feature makes the wavelet technique special from conventional time
series models (e.g., vector autoregression model, BEKK or DCC GARCH approach),
as it can capture the linkages over various time scales, thereby allowing investors
with heterogenous holding periods to examine the risk spillover between bitcoin and
financial assets (Reboredo and Rivera-Castro, 2013). Investors tend to have differ-
ent preferences toward investment horizons depending on their risk tolerance levels,
assemblation and absorption of information, and institutional constraints (Chakrabarty
et al. 2015). Moreover, the method can be applied even if the two time series are
nonlinear, non-stationary, or have structural breaks, and seasonal or cyclical patterns
(Crowley, 2005; Roueff and Sachs, 2011).

We also use another method that gauges the dynamic frequency-domain connected-
ness recently provided by Barunik and Ellington (2020a, b) and Barunik et al. (2021).
This method gives the information spillover between two-time series in different fre-
quency domains across the sample period. It is worth mentioning that Barunik and
Ellington’s (2020a, b) and Barunik et al. (2021) approach is an extension to the Diebold
and Yilmaz (2014) technique as it incorporates the stationary time-varying parameter
vector autoregressions (TVP-VAR) model.

In the following, we provide a brief overview of these three approaches.

3.1 Linear Granger causality

As a preliminary analysis, we first performed the Granger causality network method
proposed by Billio et al. (2012). This method is based on pairwise Granger Causality
measures. Let $R_{it}$ and $R_{jt}$ be two stationary time series variables; the Granger causality
can then be formulated through linear regression with the following model:

\[
R_{i,t+1} = \alpha_i R_{it} + b_{ij} R_{jt} + e_{i,t+1} \\
R_{j,t+1} = \alpha_j R_{jt} + b_{ji} R_{it} + e_{j,t+1}
\]

(1)

where $e_{i,t+1}$ and $e_{j,t+1}$ are two uncorrelated sources of white noise with its past values,
and $\alpha_i$, $\alpha_j$, $b_{ij}$, and $b_{ji}$ are coefficients of the model. According to the model in
Eq. (1), $j$ Granger-causes $i$ if $b_{ij} \neq 0$. Likewise, $i$ Granger-causes $j$ if $b_{ji} \neq 0$.2

The feedback relationships exist if the two conditions hold true. Using these indicator
variables, we are able to characterize the connecting network nodes and their direction
the directional.

2 Model in Eq. 1 is a special case of a vector autoregression, a first-order VAR.
A network of Granger-causal relations among time series can be then defined based on Eq. (1) as follows:

$$E[T_{it} | I_{st-1}] = E \left[ R_{ir} \left| \left\{ (R_{tt} - \mu_i)^2 \right\}^{t-2}_{\tau=-\infty}, R_{it-1}, R_{jt-1}, \left\{ (R_{tt} - \mu_j)^2 \right\}^{t-2}_{\tau=-\infty} \right. \right]$$

(2)

where $I_{st-1}$ is conditional system information. Then, the network of N realized volatility series can be described by the indicator of causality $(j \rightarrow i)$, where $(j \rightarrow i) = 1$ if $j$ causes $i$ and 0 otherwise. Next, we construct the Granger causality relationships as lines connecting network nodes.

### 3.2 Wavelet approach

Assume that we have two time-series named $x(t)$ and $y(t)$. Following Torrence and Compo (1998), we can obtain the cross-wavelet power spectrum with continuous wavelet transforms (CWT):

$$W_{xy}(u, s) = W_x(u, s) W_y^*(u, s)$$

(3)

In above equation, $W_x(u, s)$ and $W_y(u, s)$ denote the wavelet transforms for $x(t)$ and $y(t)$, respectively. The symbol “$^*$” refers to the complex conjugate of the basis wavelet, $u$ and $S$ reflect the position index and the smoothing operator for both time and frequency, respectively. $S(W) = S_{scale}(S_{time}(W_n(s)))$ is the smoothing approach that we get by convolution over time and scale, where $S_{scale}$ and $S_{time}$ are smoothing on the wavelet scale axis and time, respectively (Gallegati et al. 2014). The cross-wavelet power yields region of common power between two time series at each scale $s$ and time $t$ (Grinsted et al. 2004). Put differently, it reflects the local covariance between the two-time series in a time frequency fashion over the sample period.

In order to normalize the cross-wavelet spectrum, we use the “wavelet coherence” (WTC) of Torrence and Compo (1998) as shown below:

$$R_{xy}^2(u, s) = \frac{|S(u^{-1} W_{xy}(u, s))|^2}{S(u^{-1} |W_x(u, s)|^2 S|W_y(u, s)|^2)}$$

(4)

To measure the significance level of the wavelet coherence, we build theoretical distribution from Monte Carlo simulations using surrogate red-noise time series (Aguiar-Conraria and Soares, 2014; Torrence and Compo, 1998). Here, $R^2(u, s)$ is squared wavelet coherence coefficient that meets the restriction $0 \leq R^2(u, s) \leq 1$ in the time–frequency space. When $R^2(u, s)$ is close to zero, we conclude that our two-time series are weakly correlated. When the value is close to one, we conclude a strong correlation.

So far, we have explained the wavelet method, which shows the local covariance between the two time series. We can determine the asset that leads the other and distinguish between negative and positive covariances by incorporating the wavelet
phase-difference analysis as Torrence and Compo (1998) provided. Accordingly, we obtain the wavelet coherence phase difference as shown below

$$\phi_{xy}(u, s) = \tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{xy}(u, s))\}}{\Re\{S(s^{-1}W_{xy}(u, s))\}}\right)$$  \hspace{1cm} (5)

Coherence is indicated by arrows inside the significant regions as shown in Fig. 2 and 3.

3.3 Dynamic frequency-domain network connectedness

Let $X_{t,T}$ to be two stationary time-series that reveal volatilities $X_{t,T} = (x_{1,t}, x_{2,t})^T$, where $x_{1,t}$ is gold realized volatility and $x_{2,t}$ is realized volatility of another financial asset,\(^3\) such that TVP-VAR (p) can be calculated by following Barunik and Ellington (2020a,b) and Barunik et al. (2021)\(^4\):

$$X_{t,T} = \Phi_1(t/T)X_{t-1,T} + \ldots + \Phi_p(t/T)X_{t-p,T} + \epsilon_{t,T}$$  \hspace{1cm} (6)

where $\Phi(t/T)$ is referred to a $(p \times 1)$ vector of time-varying coefficients, $p$ is the lag order, and $\epsilon_{t,T} = \sum_{h=-1/2}^{1/2} (t/T)\eta_{t,T}$ with $\eta_{t,T} \sim N(0, I_M)$. The TVP-VAR process has the following vector moving average (i.e., $MA(\infty)$) representation (Roueff and Sanchez-Perez, 2016):

$$X_{t,T} = \sum_{h=-\infty}^{\infty} \Psi_{T,T}(h)\epsilon_{t-h}$$  \hspace{1cm} (7)

This measure also calculates connectedness at various frequency domains (i.e., short, medium, and long term) over the sample period. Here, the parameter vector $\Psi_{T,T}(h)$, is a bounded stochastic process. Hence, the Barunik and Ellington method considers a time-varying frequency response function $\Psi_{t,T} e^{-i\omega} = \sum_{h} e^{-i\omega h} \Psi_{t,T}(h)$ which can be obtained from a Fourier transform of the coefficients $\Psi$ with $i = \sqrt{-1}$.

Using the spectral representation of the time–frequency variance decompositions, Barunik and Ellington represent the $(j,k)$th variables of dynamic horizon specific adjacency matrix $\vartheta(u, d)$ at a rescaled time $u = t_0/T$ and horizon $d = (a, b): a, b \in (-\pi, \pi)$, as:

$$[\vartheta(u, d)]_{j,k} = \frac{\sigma_{kk}^{-1} \int_0^T \left\{\sum_{j} u[j,k] e^{-i\omega} \sum_{u} \sum_{j} [\Psi(u)e^{i\omega}]_j [\Psi(u)e^{-i\omega}]_k \right\}^2 \omega e^{-i\omega} \sum_{j} [\Psi(u)e^{i\omega}]^T} {\int_{-\pi}^{\pi} \left\{\sum_{u} \sum_{j} [\Psi(u)e^{-i\omega}]_j [\Psi(u)e^{i\omega}]^T \right\}^2 \omega e^{-i\omega} \sum_{j} [\Psi(u)e^{i\omega}]_j [\Psi(u)e^{-i\omega}]_k \} \frac{d\omega}{d\omega}}$$  \hspace{1cm} (8)

\(^3\) Here, $t$ refers to a discrete-time index and $T$ refers to an additional index.

\(^4\) The discussion and notation in this section resemble those in Barunik and Ellington (2020a, b) and Barunik et al. (2021).
where \( \vartheta(u, d)_{j,k} \) represents the portion of the local error variance of the \( j \)th variable at a given frequency band given shocks in the \( k \)th variable scaled by the variance of the \( j \)th variable. Finally, total dynamic connectedness is the ratio of the off-diagonal elements to the sum of the whole matrix:

\[
C_{F, j,k}(u, d) = \frac{100}{\left( \sum_{k=1}^{N} \left[ \vartheta(u, d)_{j,k} \right] \right) \left( \sum_{j,k=1}^{N} \left[ \vartheta(u, \infty)_{j,k} \right] \right)}
\]  

(9)

Following Barunik and Krehlik (2018), Barunik and Kocenda (2019), and Barunik and Ellington (2020a,b), we estimate the dynamic frequency-domain connectedness between bitcoin and each asset under consideration, at three scales, \( C_{F, T}(u, d) \) such that the short (S), medium (M) and long term (L) investment horizons correspond to period of 1 to 5 days, 6 to 22 days, and longer than 22 days, respectively. 5

4 Data

This paper uses daily data for the realized volatility (RV) of future bitcoin contracts and the other five major asset classes of gold, oil, foreign exchange, stocks, and bonds. The data set on realized volatilities (RV) of bitcoin and the other five asset classes were obtained from the Risk Lab website as set by Professor Dacheng Xiu from the University of Chicago. 6 The data trades are collected from Tick Data Inc, which represents the highest frequency available (up to every millisecond). The professor cleaned the data by using the prevalent national best bid and offer (NBBO). He estimates the realized volatility of nonzero returns for prices sampled from the highest frequency available using quasi-maximum likelihood estimates (QMLE) of volatility built on moving-average models MA(q) (see Xiu, 2010; Da and Xiu, 2020).

The realized volatility data represent 5-min returns of future contracts for all financial assets and cover a roughly two-year period from February 3, 2019, to November 26, 2020. We choose the S&P 500 Index, USD/EUR, and US 10-year T-note futures to proxy for stock market foreign exchange rate and bond market, respectively. We use the light sweet crude oil (WTI) futures contract as a proxy for the oil market. The motivation behind choosing one year before the pandemic as the start date is to merge and compare the volatility interdependence during two different economic situations, namely during a relatively stable economic period (February 2019 to December 2019) and during the COVID-19 outbreak (January 2020 to November 2020). 7 Looking at Fig. 1, we can clearly see that all the five asset classes maintain relatively stable

5 These definitions of time–frequency bands represent investors’ perspectives at different investment horizons (Barunik and Kocenda, 2019). Specifically, the short-term investment horizon represents a business week, the medium-term investment horizon represents a business month, and finally, the long-term investment horizon represents a business year.

6 The data are available from: https://dachxiu.chicagobooth.edu/.

7 Goodell and Goutte (2021), Kamaludin et al. (2021), Vidal-Tomas (2021), Huang, Duan, and Mishra (2021) used similar time-frame in analyzing the impact of the COVID-19 pandemic on the spillovers between financial assets.
volatility before the pandemic. However, their volatility jumped dramatically during the pandemic. The price of Bitcoin witnessed acute decreases in March 2020. Conlon and McGee (2020) do not support safe-haven properties of Bitcoin as its price decreases alongside the S&P 500 index. Our study focuses on volatility, rather than return, connectedness between Bitcoin and financial assets covering a longer period during the COVID-19.

5 Empirical analysis

Table 1 reports the descriptive statistics about daily realized volatility during our sample period. Bitcoin has the highest mean and median values, suggesting that it may not be used as currency due to its high fluctuation (see, for example Baur and Dimpfl 2021). On average, the standard deviation also increases when the mean volatility increases. This finding supports the long memory in which all volatility of volatility increases when realized volatility is high (Barndorff-Nielsen and Shephard, 2005). The standard deviation of oil volatility is the greatest, with 0.416. This can be seen clearly through oil’s extreme values during the pandemic. According to Table 1, there is a high dispersion between the minimum and maximum values (0.116 and 3, respectively). According to Fig. 1, oil volatility rose sharply during the early period of the pandemic, between March and May 2020. This finding can be at least attributed to the drop in
| Asset      | Mean   | Median | Maximum | Minimum | Std. Dev | Skewness | Kurtosis | J-B     | ADF    |
|------------|--------|--------|---------|---------|----------|----------|----------|---------|--------|
| Bitcoin    | 0.5212 | 0.4653 | 1.9337  | 0.0819  | 0.2704   | 1.7090   | 7.2756   | 471.91***| -7.124***|
| Gold       | 0.1501 | 0.1355 | 0.5798  | 0.0570  | 0.0713   | 2.0251   | 10.3387  | 1106.58***| -3.177** |
| USD/EUR    | 0.0593 | 0.0552 | 0.1774  | 0.0184  | 0.0227   | 1.4173   | 6.5398   | 323.89***| -3.283** |
| S&P 500    | 0.1982 | 0.1515 | 1.1472  | 0.0478  | 0.1414   | 2.8890   | 14.9668  | 2781.29***| -3.367** |
| US Bond    | 0.0411 | 0.0371 | 0.1558  | 0.0167  | 0.0182   | 2.3323   | 12.7966  | 1854.26***| -4.929***|
| Oil        | 0.4505 | 0.3290 | 3.0000  | 0.1166  | 0.4164   | 3.6163   | 18.0176  | 4375.96***| -3.177** |

The table reports summary statistics for daily-realized volatility of all assets under examination for the sample period from February 3, 2019 to November 26, 2020. The daily-realized volatility is calculated using 5-min intraday data for each series. J-B is the Jarque–Bera statistic tests for normality of the series. Asymptotic ADF critical values are -3.447, -2.869, and -2.570 for 1%, 5%, and 10% significance levels, respectively. *** and ** denote significance at the 1% and 5% levels, respectively.
oil price below zero in April 2020 due to the decrease in world industrial production in the first quarter of 2020 (Gharib et al. 2020; Bakas and Triantafyllou, 2020).

The volatility of US equity or S&P 500 shows a similar trend. The mean volatility of foreign exchange and US bond is the lowest. In contrast, gold volatility is higher, which is not consistent with the conventional safe-haven argument when investing in gold during crises (see Tully and Lucey, 2007; and Shafiee and Topal, 2010). The daily volatility distribution for all assets is not normal, as indicated by Jarque–Bera (JB, 1987) test. The values from this test are high and significant at a one percent level, thereby rejecting the null hypothesis of a normal distribution. This is also evident by nonzero values for skewness and more significant than three values for Kurtosis. This should not be surprising, especially for bitcoin, as several studies found that its price exhibits bubble-like dynamics and extreme price movements (Corbet et al. 2019, 2018; Urquhart, 2017). Our volatility series are stationary since the Augmented Dickey-Fuller (ADF, 1979) test rejects the null hypothesis of non-stationary.

As shown in Fig. 1, all financial assets, except bitcoin, shows relatively stable volatility before the pandemic. The daily volatility did not exceed 0.3, 0.15, 0.4, 0.1, and 0.5 for gold, foreign exchange, S&P 500, bonds, and oil, respectively, before the pandemic. Their volatility jumped to 0.6, 0.17, 1.2, 0.15, and 3 during the pandemic, particularly between March and April 2020. Bitcoin volatility, however, witnessed the highest volatility before the pandemic. These findings are consistent with previous research documenting an increase in market volatility during the pandemic (e.g., Ali et al. 2020; Apergis and Apergis 2020; Gil-Alana and Monge 2020). Bitcoin shows the greatest volatility clustering, a feature that characterizes this cryptocurrency (Cont 2001).

Figure 2 presents the correlation heatmaps between realized volatility of the six financial assets. The warmer the color (red), the higher the correlation. Before the pandemic, Bitcoin was weakly correlated with all assets, but the correlation increased to around 0.4. Similarly, the correlation between the financial assets increased during the pandemic except for the US bond, where it increased only with Bitcoin. The correlation between the volatilities of US bonds, gold, and oil has declined amid the pandemic. These findings imply that Bitcoin may not provide a good hedging opportunity arising from including it in bond portfolios.

Figure 3 displays a 22-day rolling correlation between realized volatility of bitcoin and each of the five financial assets. The correlation process starts from the first 22 days window and lasts until the end of the sample period. The figure confirms the time-varying association that increases sharply during specific periods. There are similarities in the volatility correlation between Bitcoin- gold and Bitcoin-foreign currency. They both increase simultaneously (for example, January, July, and September 2020). Bitcoin experienced extreme co-movements with bonds and oil with a correlation that exceeded 0.75 during February 2020. Bitcoin and oil correlation is generally low and reached a significant level only during the early period of the pandemic (February and March 2020). Overall, the correlation between Bitcoin and financial assets is time-varying and non-synchronous.

8 The two periods in which bitcoin volatility was at the most significant level were from late 2013 to early 2014 and 2017, Chaim and Laurini, 2018. These two periods are not covered in our sample period.
As a preliminary test, we use the linear Granger causality connectedness measure proposed by Billio et al. (2012). The Granger causality connectedness among our realized volatility series are drawn as lines connecting network nodes. The size of the node can reflect the scale of connectedness based on the Granger causality relationship, which is an indication of systematic importance. Figure 4 presents the visualization of the network graph among the realized volatility (RV) of bitcoin contracts and the other five major asset classes during our sample period. It shows that bitcoin volatility is weakly connected with the other assets’ volatility. However, the most crucial cluster in the network is centered on S&P 500.

Figure 5 displays the cross-wavelet transform (XWT) analysis between bitcoin volatility and each financial asset, indicating the two variables’ common power without normalization in the wavelet power spectrum. The horizontal and left vertical axes define the time and frequency dimensions (period-scales in terms of days). The color bar to the right indicates the steep power gradient of the significant contours. Significant areas lie within the thick black curve, significant at 5% level (95% confidence) obtained from the Monte Carlo simulations using the phase randomized surrogate series. Warmer colors (yellow) indicate the highest power (strong correlations), while colder colors (blue) indicate the lowest power (weak correlations). The direction of relevance and a lead-lag relationship are shown as arrows. If arrows point to the up and right, then bitcoin volatility is leading to other financial asset volatility. If arrows
Fig. 3 Rolling window correlation. Notes This figure presents 22-day rolling correlation between realized volatility of bitcoin and one of the financial assets (gold, oil, foreign currency, stock and bond markets).

point to the down and right, Bitcoin volatility is lagging. If arrows point to the down and left, then bitcoin volatility leads while lagging if arrows point to the up and left.

By looking at the thick black curves and the power of color (yellow reflects stronger correlation), we know the degree of volatility connectedness between the assets. Generally, bitcoin volatility is not strongly correlated with the other assets’ volatility. For
the bitcoin-gold pair, the strong and significant correlation is limited at a time scale between 64 and 128 days (i.e., long-horizon). In this pair, bitcoin volatility is lagging.\footnote{Since the volatility is lagging, then market participants can predict the volatility of Bitcoin using the volatility of gold at this time–frequency.}

There is almost no strong and significant correlation for bitcoin-foreign exchange pair at any time scale and period before the pandemic. Although foreign exchange is regarded as a means of payment, bitcoin can be used as a speculative investment. Therefore, it may share more fundamentals with other assets such as bonds, stocks, and commodities (Baur et al. 2018). For the bitcoin-S&P 500 pair, we notice a weak correlation that is statistically significant at the short-time horizon (between 4- and 8-day scale) but a stronger correlation in the long term. Bitcoin has relatively greater volatility interdependence with bonds in the long-term horizon. In most volatility pairs, it is evident that significant correlation occurs during the early period of the pandemic.

The reason that bitcoin volatility exhibits lead or lag relation with financial assets are attributed to the potential drivers of Bitcoin prices. According to Kristoufek (2020), these drivers are related to the demand for the currency, speculation, and technical factors. Bitcoin characteristics from these divers are complex and evolve over time. For example, Bitcoin can be regarded as an acceptable means of payment in some periods, while in other periods, it can be used for investment speculation purposes. When Bitcoin is used for the former (latter) reason, we may expect that its volatility may lag (lead) the volatility of financial assets. These findings are useful for predicting the volatility of Bitcoin (in case if its volatility is lagging) or the volatility of financial assets (when its volatility is leading).

Our previous test could be affected by a common power of two processes without normalization to the single wavelet power spectrum (Andries et al. 2014). Hence, our volatility interlinkage may not be accurate if one asset volatility spectra are local and

\textbf{Fig. 4} Network diagram of linear Granger-causality. \textit{Notes:} Linear Granger-causality-based estimated based on Billio et al. (2012)
COVID-19 and the volatility interlinkage between bitcoin and financial assets

Fig. 5 Cross-Wavelet Transform (XWT). Note: The figure plots the cross-wavelet transform of the pairs of realized volatilities (gold/other financial assets). The horizontal and left vertical axes define the time and frequency dimensions (period-scales in terms of days), respectively. The color bar to the right indicates the steep power gradient of the significant contours. Significant areas lie within the thick black curve, which is significant at 5% level (95% confidence) obtained from the Monte Carlo simulations using the phase randomized surrogate series. Warmer colors (yellow) indicate highest power (strong correlations), while colder colors (blue) indicate lowest power (weak correlations). The phase relationship between the two-time series is shown as arrows with in-phase pointing right and anti-phase pointing left.

The results of volatility wavelet coherence between bitcoin and other financial assets are qualitatively similar and consistent with what we find from the XWT analysis. Overall, the bitcoin volatility is not at high coherence with other assets’ volatility.
most of the volatility pairs, it is evident that significant coherence occurs mainly during the early period of the pandemic and at the long-term horizon. Further, the arrows on the figures, especially for gold, bonds, stocks, and foreign currency, in contrast to oil, generally point to the right (→). This indicates an in-phase or positive correlation in volatility between bitcoin and the financial assets.

The figure shows a more evident lead-lag volatility dependence between bitcoin and financial assets relative to Fig. 4. During the pandemic between January and July 2020, bitcoin volatility is generally leading gold volatility, that arrows are in the majority ↑, while lagging, that arrows are in the majority ↓, after July at a time scale between 8 and 16 days. Before the pandemic, the volatility interdependence was negative, that arrows are in the majority ← and limited at narrow periods. Therefore, the pandemic increased the volatility association between bitcoin and gold. In contrast to our finding in Fig. 4, there is a significant volatility interlinkage between bitcoin
and foreign exchange but mainly at short-term and medium-term horizons during the pandemic. Like the bitcoin-gold pair, the volatility of bitcoin is negatively related to the volatility of foreign exchange before the pandemic. Thus, we may conclude that the pandemic changed the bitcoin volatility interlinkage more with gold and foreign exchange. There is almost no significant wavelet coherency between the volatility of bitcoin and the S&P 500. The volatility of bonds leads to bitcoin’s volatility at a time scale between 4- and 8-days during March and April 2020. Finally, for the bitcoin-oil pair, the volatility coherence is limited and only exists during the pandemic, mainly at the short-term horizon in the early period (January to May 2020) and at the intermediate horizon in the later period (during November 2020).

So far, we have examined the lead-lag volatility connection using wavelet analysis. Although we know whether the relation is in-phase or anti-phase, it is hard to determine the exact amount of connectedness. To do so, we use the dynamic frequency-domain connectedness. In Fig. 7, we observe that the pandemic caused the greatest effect on volatility connectedness between bitcoin and gold over two periods, the first is between

Fig. 7 Dynamic frequency-domain connectedness. Notes: The figure plots the dynamic frequency-domain connectedness index within one standard-deviation percentiles. The index indicates the total information flow of realized volatility between two assets. The index measures at short- (1 to 5 days) (medium-6 to 22 days), and long-term horizons (longer than 22 days)
January and April (during the first wave of the COVID-19 crisis), and the second is between May and July (the second wave of the pandemic). In these two periods, the amount of connectedness reached nearly 20% and 35%, respectively.\textsuperscript{10} The source of this connectedness originates mainly during the short-term horizon. Similarly, the volatility relation between bitcoin and foreign currency mainly comes from short-term connectedness, and it witnessed two peaks during the pandemic. In contrast, the volatility connectedness for bitcoin-oil and bitcoin-S&P 500 pairs comes mainly from the intermediate-term during the pandemic rather than from the short term. Finally, the connectedness between bitcoin and bond volatility is small and rarely exceeds 10%. The pandemic has no discernable effect on their volatility relation. Our findings can extend prior work, Mensi et al. (2020), who document diversification benefits from investing in bitcoin along with conventional and Islamic stock markets for short-term investors. Here, we show that bitcoin can diversify risk for long-term investors when invested with specific assets such as bonds, gold, and foreign currency. Our findings also extend prior work documenting the dynamic correlation between Bitcoin return and assets returns. Damianov and Elsayed (2020) show that despite a low Bitcoin correlation with financial assets, its optimal weight in the minimum variance portfolio is small (around 1 percent). A similar conclusion is reached by Bouri, et al. (2017b). Thus, they do not support the notion that Bitcoin is a strong, haven or hedger asset given its high volatility.

Overall, the findings conclude with the following. First, the effect of the pandemic on volatility interdependence between Bitcoin and financial assets is concentrated at an early stage of the pandemic. Second, the pandemic caused a high increase in volatility interdependence of Bitcoin – gold and foreign currency pairs. Third, volatility interdependence between bitcoin and financial assets is at the most significant level in the long term before the pandemic. However, during the pandemic, the volatility connectedness has increased for certain assets in the short or long term.

5.1 Hedge ratios and portfolio weight

After deciphering the extent of volatility shocks spillover between Bitcoin and financial assets, we suggest risk management methods including hedge ratios and optimal weights that minimize portfolio variance at different time horizons. Following the related literature (Kroner and Sultan 1993; Kroner and Ng 1998; Basher and Sadorsky 2016; Maghyereh et al. 2017; Antonakakis et al. 2018; Maghyereh et al. 2018; Maghyereh et al. 2019), we use conditional variance estimates (DCC-GARCH) to construct hedge ratios and optimal portfolio weights.

We first consider the hedging problem of a one-dollar portfolio containing a long position in Bitcoin ($i$) and a short position in one of the financial assets ($j$) that minimize risk while preserving the level of expected returns. This minimization problem is given by

$$
\min_{\beta_i} \text{var}(r_{pt}) = \min_{\beta_i} \left\{ \text{var}(r_{it}) + \beta_i^2 \times \text{var}(r_{jt}) + 2 \beta_i \times \text{cov}(r_{it}, r_{jt}) \right\}
$$

\textsuperscript{10} Note that the connectedness reached the highest level in mid-July during the peak of the second wave of the coronavirus pandemic but declined sharply subsequently.
By solving the risk-minimizing problem (using first-order and second-order derivatives of \( var(r_{pt}) \)), the time-varying optimal hedge ratio \( \beta_{ij,t}^* \) is as follows:

\[
\beta_{ij,t}^* = \frac{Cov(r_{it}, r_{jt})}{\text{var}(r_{jt})} = \frac{h_{ij,t}}{h_{jj,t}}
\]

(11)

In Eq. 11, a \( \beta_{ij,t}^* \) closer to zero indicates that the financial asset is a cheap hedge for Bitcoin. As such, the optimal weight \( w_{ij,t}^* \) for a two-asset portfolio \( (i, j) \) is obtained by:

\[
w_{ij,t}^* = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}, \text{ with } w_{ij,t}^* = \begin{cases} 
0, & \text{if } w_{ij,t}^* < 0 \\
\frac{w_{ij,t}^*}{1}, & \text{if } 0 \leq w_{ij,t}^* \leq 1 \\
1, & \text{if } w_{ij,t}^* > 1
\end{cases}
\]

(12)

where \( w_{ij,t}^* \) is weight of the asset \( i \) in a one-dollar portfolio at time \( t \), \( h_{ij,t} \) is the conditional covariance between \( i \) (i.e., returns on Bitcoin) and \( j \) (i.e., one of the financial assets returns) at time \( t \); \( h_{ii,t} \) and \( h_{jj,t} \) are the conditional variances of \( i \) and \( j \), respectively. The weight of asset \( j \) in the considered portfolio is computed by \( (1 - w_{ij,t}^*) \).

Finally, we can examine the risk-minimization effectiveness of each portfolio containing bitcoin and one of the financial assets using the hedge effectiveness (HE) metric as follows:

\[
HE = 1 - \frac{h_{\text{hedged}}}{h_{\text{unhedged}}}
\]

(13)

where \( h_{\text{hedged}} \) is the return variance of the weighted portfolio containing bitcoin and one of the financial assets, whereas \( h_{\text{unhedged}} \) is the return variance of the benchmark portfolio (without any diversification), a higher HE ratio indicates a greater hedging effectiveness.

Table 2 duplicates the summary statistics of hedge ratios, optimal portfolio weights, and HE over the sample period using wavelet transformed data at the three frequency horizons (short (1–5 days), medium (6–22 days), and long term (longer than 22 days)). As shown in Panel A, the hedge ratio of a $1 long position in the Bitcoin requires a short position of 0.87, 1.88, 0.42, −0.15, 0.09 cents in gold, foreign currency, S&P 500, US Bond, and oil, respectively. Oil is the cheapest hedge for Bitcoin in the short, medium, and long term. The highest risk-reduction in oil volatility can be reached with gold, followed by S&P 500. They provide hedging effectiveness (HE) of 21% and 16%, respectively. The table shows an increase in the optimal weight during the long term, indicating that a higher portfolio allocation weight to Bitcoin is needed.

The changing dynamic of risk transfer during the COVID-19 pandemic suggests that the hedge ratio and optimal portfolios are likely to differ over the sample period. Hence, Table 3 shows the same analysis performed in two periods: pre-COVID-19 (Panel A), and during COVID-19 (Panel B) for a short-horizon (1–5 days). Tables 4 and 5 show the results for a medium term (6–22 days) and long term (more than
Table 2 Hedge ratios and portfolio weights over the sample period

| Portfolio weight | Hedging |
|------------------|---------|
| Optimal weight   | HE (%)  | Hedge ratio | HE (%) |

**Panel A. Short-horizon [1–5 days]**

| Asset Pair          | Optimal weight | HE (%) | Hedge ratio | HE (%) |
|---------------------|----------------|--------|-------------|--------|
| Bitcoin/Gold        | 0.04           | 95     | 0.87        | 21     |
| Bitcoin/USD/EUR     | 0.01           | 99     | 1.88        | 11     |
| Bitcoin/S&P 500     | 0.08           | 92     | 0.42        | 16     |
| Bitcoin/US Bond     | 0.07           | 94     | −0.15       | 2      |
| Bitcoin/Oil         | 0.38           | 66     | 0.09        | 13     |

**Panel B. Medium-horizon [6–22 days]**

| Asset Pair          | Optimal weight | HE (%) | Hedge ratio | HE (%) |
|---------------------|----------------|--------|-------------|--------|
| Bitcoin/Gold        | 0.08           | 0.94   | 1.53        | −70    |
| Bitcoin/USD/EUR     | 0.03           | 0.99   | 3.03        | −269   |
| Bitcoin/S&P 500     | 0.13           | 0.82   | 0.96        | 27     |
| Bitcoin/US Bond     | 0.11           | 0.93   | −0.82       | −167   |
| Bitcoin/Oil         | 0.36           | 0.17   | 0.61        | 10     |

**Panel C. Long-horizon [longer than 22 days]**

| Asset Pair          | Optimal weight | HE (%) | Hedge ratio | HE (%) |
|---------------------|----------------|--------|-------------|--------|
| Bitcoin/Gold        | 0.13           | 81     | 0.53        | −188   |
| Bitcoin/USD/EUR     | 0.04           | 99     | 0.91        | −159   |
| Bitcoin/S&P 500     | 0.17           | 85     | 0.83        | −243   |
| Bitcoin/US Bond     | 0.13           | 95     | −0.53       | −197   |
| Bitcoin/Oil         | 0.63           | 31     | −0.32       | −32    |

The table reports average optimal weights and hedge ratios between pairs of assets in 1$ portfolio. Panel A for short-horizon (1–5 days), Panel B for medium-horizon (6–22 days), and Panel C for long-horizon (longer than 22 days).

Pre the pandemic, a $1 long position in Bitcoin requires a short investment position of 28 cents in gold, 1.71 dollars in foreign exchange, 4 cents in S&P 500, -0.49 cents (or long position of 0.49 cents) in US Bond, 3 cents in oil in the short term. Hedging requirements increase during the pandemic to 1.21 dollars, 1.77 dollars, 77 cents, 14 cents, and 77 cents in gold, foreign currency, S&P 500, US bond, and oil, respectively. Therefore, hedging Bitcoin is more costly during the pandemic yet more effective when using gold, foreign currency, and S&P 500 as indicated by the hedging effectiveness variable (HE). These assets became even more effective in the medium term than the remaining ones. For example, a long position in Bitcoin requires a short position in bonds by 14 cents in the short term, while it requires a long position by 60 cents in the medium term. Therefore, hedging Bitcoin is more costly during the pandemic yet more effective when using gold, foreign currency, and S&P 500 as indicated by the hedging effectiveness variable (HE).

Figure 8 shows the time-varying hedging ratio in the short medium and long terms. According to the figure, hedge ratios are considerably volatile over the sample period (the highest is for the Bitcoin-oil pair). Moreover, they reached a peak during the early period of the pandemic (March and April 2020), indicating that an increase in
Table 3 Short-horizon portfolio analysis: two subsamples (pre- and during pandemic)

| Portfolio weight | Hedging |
|------------------|---------|
|                  | Optimal weight | HE (%) | Hedge ratio | HE (%) |
| Panel A. Pre-pandemic [Feb 3, 2019 to Dec 31, 2019] | | |
| Bitcoin/Gold     | 0.03     | 98     | 0.28        | 18     |
| Bitcoin/USD/EUR  | 0.01     | 100    | 1.71        | 14     |
| Bitcoin/S&P 500  | 0.05     | 97     | 0.04        | 7      |
| Bitcoin/US Bond  | 0.05     | 98     | 0.49        | 17     |
| Bitcoin/Oil      | 0.22     | 85     | 0.03        | 10     |
| Panel B. During pandemic [Jan 1, 2020 to Nov 26, 2020] | | |
| Bitcoin/Gold     | 0.05     | 0.92   | 1.21        | 28     |
| Bitcoin/USD/EUR  | 0.01     | 0.98   | 1.77        | 11     |
| Bitcoin/S&P 500  | 0.11     | 0.84   | 0.77        | 22     |
| Bitcoin/US Bond  | 0.11     | 86     | 0.14        | -3     |
| Bitcoin/Oil      | 0.58     | 100    | 0.17        | 1      |

The table reports average optimal weights and hedge ratios for pairs of assets in 1$ portfolio. Panel A presents the results pre COVID-19, and Panel B shows the results during the COVID-19, both for a short-horizon of 1–5 days.

Table 4 Medium-horizon portfolio analysis: two subsamples (pre- and during pandemic)

| Portfolio weight | Hedging |
|------------------|---------|
|                  | Optimal weight | HE (%) | Hedge ratio | HE (%) |
| Panel A. Pre-pandemic [Feb 3, 2019 to Dec 31, 2019] | | |
| Bitcoin/Gold     | 0.06     | 96     | 2.92        | -81    |
| Bitcoin/USD/EUR  | 0.01     | 100    | 7.29        | -170   |
| Bitcoin/S&P 500  | 0.07     | 97     | 2.50        | -128   |
| Bitcoin/US Bond  | 0.10     | 95     | 1.12        | -84    |
| Bitcoin/Oil      | 0.17     | 70     | 0.87        | -155   |
| Panel B. During pandemic [Jan 1, 2020 to Nov 26, 2020] | | |
| Bitcoin/Gold     | 0.12     | 91     | 0.44        | -90    |
| Bitcoin/USD/EUR  | 0.05     | 98     | 0.17        | -341   |
| Bitcoin/S&P 500  | 0.24     | 65     | -0.09       | 34     |
| Bitcoin/US Bond  | 0.13     | 91     | -0.60       | -311   |
| Bitcoin/Oil      | 0.63     | 39     | 0.41        | -16    |

The table reports average optimal weights and hedge ratios for pairs of assets in 1$ portfolio. Panel A presents the results pre COVID-19, and Panel B shows the results post COVID-19, both for a medium-horizon (6–22 days).
Table 5 Long-horizon portfolio analysis: two subsamples (pre- and during pandemic)

| Portfolio weight | Hedging |
|------------------|---------|
|                  | Optimal weight | HE (%) | Hedge ratio | HE (%) |
| Panel A. Pre-pandemic [Feb 3, 2019 to Dec 31, 2019] |
| Bitcoin/Gold     | 0.29     | 80     | −5.31e+05   | −100   |
| Bitcoin/USD/EUR  | 0.07     | 98     | 1.44e+05    | −380   |
| Bitcoin/S&P 500  | 0.33     | 71     | 3.58e+02    | 2051   |
| Bitcoin/US Bond  | 0.15     | 86     | −4.30e+05   | 946    |
| Bitcoin/Oil      | 0.73     | −34    | −3.53e+04   | 547    |
| Panel B. During pandemic [Jan 1, 2020 to Nov 26, 2020] |
| Bitcoin/Gold     | 0.04     | 91     | 5.17        | −15    |
| Bitcoin/USD/EUR  | 0.04     | 99     | 7.15        | 338    |
| Bitcoin/S&P 500  | 0.29     | 81     | −67.37      | 47     |
| Bitcoin/US Bond  | 0.17     | 86     | 67.70       | 47     |
| Bitcoin/Oil      | 0.51     | 30     | −8.02       | 18     |

The table reports average optimal weights and hedge ratios for pairs of assets in 1$ portfolio. Panel A presents the results pre COVID-19, and Panel B shows the results post COVID-19, both for a long-horizon (longer than 22 days).

the number of contracts is required for hedging Bitcoin shocks. However, this does not hold for the Bitcoin-foreign currency as the hedge ratio almost does not increase during the pandemic in the short term, but it does in the medium and long term. The peaks in the hedging ratio reach a higher level in the long term.

6 Conclusion

Bitcoin diversification ability is questioned in the literature. Several studies indicate that bitcoin is more volatile than other assets such as gold, currencies, and bonds (e.g., Smales 2019). COVID-19 pandemic represented the major crisis after the active trading of bitcoin futures in December 2017. Accordingly, we investigate the pandemic effect on volatility interlinkages between bitcoin and major asset classes (oil, foreign exchange, gold, stocks, and bonds).

We document that bitcoin volatility is high and increases during the pandemic supporting its speculative behavior (Gandal et al. 2018; Corbet et al. 2018). More importantly, bitcoin volatility connectedness with bonds is weak and almost not affected by the pandemic. Moreover, the volatility connectedness between bitcoin and gold and foreign exchange is limited to short and intermediate terms.

After deciphering the extent of volatility shocks spillover between Bitcoin and financial assets, we suggest risk management methods including hedge ratios and optimal weights that minimize portfolio variance at different time horizons. Our findings offer practical investment implications. For instance, given the potential losses
Fig. 8 Time-varying hedge ratios. Note: The figure plots the dynamic frequency-domain hedge ratios. The hedge ratios are measured at short- (1 to 5 days) medium- (6 to 22 days), and long-term horizons (longer than 22 days).
from having volatile assets during the pandemic, investors may consider investing in oil along with bitcoin to diversify the pandemic risk. Oil is the cheapest hedge for Bitcoin in the short, medium, and long term. We also find that hedging Bitcoin was more costly during the pandemic yet became more effective when using gold, foreign currency, and S&P 500.

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**Authors’ contributions** The first author handled the code and results creation. The second author handled the results analysis and writing the original draft. Both authors handled the review and editing of the final draft.

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