Investigating the relationship between volatilities of cryptocurrencies and other financial assets

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Abstract
This paper analyzes the relationships between volatilities of five cryptocurrencies, American indices (S&P500, Nasdaq, and VIX), oil, and gold. The results of the BEKK-GARCH model show evidence of a higher volatility spillover between cryptocurrencies and lower volatility spillover between cryptocurrencies and financial assets. The results of the DCC-GARCH model identify an important effect of the launch of Bitcoin futures. During the stability period, the overarching implications of the results are that there is a persistence of correlation between cryptocurrencies in high positive value and low dynamic conditional correlations between cryptocurrencies and financial assets. Also, we find that Bitcoin and gold are considered hedges for the US investors before the coronavirus crisis. Our results show that cryptocurrencies may offer diversification benefits for investors and are diversifiers during the stability period. At the beginning of 2020, we observe that the conditional correlation increased between cryptocurrencies, stock indexes, and oil which confirm the effect of the coronavirus contagion between them. Unlike gold, digital assets are not a safe haven for US investors during the coronavirus crisis.

Keywords Cryptocurrencies · Bitcoin · Gold · Oil price · VIX · Stock market · COVID-19 pandemic

JEL Classification G0 · G1 · F3

1 Introduction
The covid-19 outbreak and Russia–Saudi Arabia oil price war have destabilized the global economic and financial system in the first quarter of 2020. International stock markets, futures, and crude oil prices dropped successively. Since the breakdown of

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Bretton Woods, gold does not have the same prominence in the international monetary system. However, it still attracts considerable attention from investors, media, and researchers. Especially, during the global economic and financial crisis that started in 2007 with the subprime mortgage market crisis in the USA, the gold price has recorded an intense increase while other assets had losses (Beckmann et al. 2015). In recent years, correlations among most types of assets increased significantly. However, gold is still considered to be a zero-beta asset (McCown and Zimmerman 2006) and is often said to be uncorrelated with other assets (Baur and Lucey 2010). Oil is a raw material, while gold is a precious metal. Tiwari and Sahadudheen (2015) explored the relationship between real oil prices and real gold prices. They found that oil has the lowest average return, while gold has the highest average return. Similarly, oil has the highest volatility, whereas gold has the lowest volatility. They employed many types of GARCH models and find that shocks in gold prices have an asymmetric effect, which means that positive and negative shocks have different effects on gold prices in terms of magnitude.

Dyhberg (2016a) claimed that the global uncertainty surrounding the 2007 global financial crisis eased the emergence of the first decentralized cryptocurrency based on the blockchain technology named Bitcoin and strengthened its popularity. Nakamoto (2008) designed Bitcoin. It facilitated electronic payments between individuals without going through a third party. Bitcoin has been the subject of challenges and opportunities for policymakers, consumers, entrepreneurs, and economists since its introduction. Bitcoin is considered to be different from any other asset in the financial market. It creates new possibilities for stakeholders with regard to portfolio analysis, risk management, and consumer sentiment analysis (Dyhberg 2016a). Bitcoin is compared to gold because they have many similarities. Neither of them has a nationality or is controlled by a government. They are mined by several independent operators and companies. Gold has some intrinsic values but most likely it does not justify its current market value (Dyhrberg 2016b). Bitcoin is defined as a highly volatile asset (Brière et al. 2015; Selmi et al. 2018; Symitsi and Chalvatzis 2019; Agosto and Cafferata 2020; Giudici and Pagnonetti 2020; Baur and Hoang 2020). It has become a main theme in the financial press and academia. Given the acceptance of Bitcoin as an investment and its rising importance, modeling Bitcoin price volatility becomes important to investment decisions and risk management (Katsiampa 2017). Many studies used the GARCH- family models as the backbone of modeling Bitcoin’s volatility (Katsiampa 2017; Bouri et al. 2017; Guesmi et al. 2019; Fakhfekh and Jeribi 2020). Glaser et al. (2014) and Gronwald (2014) have employed linear GARCH. Dyhrberg (2016b), Bouoiyour and Selmi (2015, 2016) and Bouri et al. (2017) have used the Threshold GARCH (TGARCH). Using asymmetric GARCH models, Bouri et al. (2017), Katsiampa (2017), Baur et al. (2018), and Stavroyiannis (2018) investigated the response of the conditional variance to past positive and negative shocks and find an inverted leverage effect.

At the same time, another line of research is interested in studying the correlation between conventional asset classes and Bitcoin. Modeling the dynamic volatilities of cryptocurrencies and other assets is an important and new subject to study because of recent developments in increased integration between financial markets. Various studies use a number of methods and find that Bitcoin is very weakly associated with
conventional assets such as bonds, commodities, and equities (e.g., Bouri et al. 2017; Gajardo et al. 2018; Klein et al. 2018; Bouri et al. 2020). Based on the MVQM-CAViaR approach, Wang et al. (2019) show that the impact of the VIX shocks on Bitcoin’s risks is negligible. However, Jareno et al. (2020) show negative and statistically significant effects of VIX on Bitcoin returns. While Bitcoin is still perceived to be mysterious and not very well understood by many financial market stakeholders. The analysis of Bitcoin’s capabilities in terms of different financial aspects must be carried out. Two observations are considered from the above studies. First, the Bitcoin volatility has received a lot of attention in most studies using the GARCH family models. Second, the relationships between Bitcoin and conventional asset classes are discussed somewhat, especially during the COVID-19 outbreak. However, the existing literature lacks a clear understanding of the Bitcoin’s volatility. It also lacks evidence of relationships between other cryptocurrencies and conventional asset classes.

Most of the researches that studied volatility dynamics and correlations between Bitcoin and other assets have used multivariate GARCH models like BEKK-GARCH (Klein et al. 2018; Corbet et al. 2018), DCC-GARCH (Bouri et al. 2017), or ADCC-GARCH (Kumar and Anandarao 2019; Gajardo et al. 2018; Tiwari et al. 2019). Most of the works focused on Bitcoin as the cryptocurrency market’s leader. A number of new cryptocurrencies appeared and most of them are developed further on the basis of blockchains. Previous studies like Baur and Dimpfl (2018), Phillip et al. (2018), and Fakhfekh and Jeribi (2020) were interested in modeling the volatility dynamics of cryptocurrencies. However, a small number of studies have investigated volatility transmission between Bitcoin and other cryptocurrencies (Katsiampa et al. 2019; Beneki et al. 2019). Agosto and Cafferata (2020) investigated the relationships between the explosive behaviors of cryptocurrencies through a unit root testing approach. They confirmed the presence of high interdependence in the cryptocurrency market as in Corbet et al. (2018) and Yi et al. (2018). Aslanidis et al. (2019) studied the conditional correlations between four cryptocurrencies (Bitcoin, Monero, Dash, and Ripple), S&P 500, bond, and gold. The results indicated that the studied cryptocurrencies are strongly correlated. However, the associations between cryptocurrencies and conventional financial assets are negligible. Tiwari et al. (2019) investigated time-differentiated correlations between the S&P 500 and six other cryptocurrencies. They suggested that cryptocurrencies are perceived to be a hedge against the risks of the S&P 500. Charfeddine et al. (2020) investigated the dynamic relationship between Bitcoin and Ethereum and major financial commodities and securities. They supported the idea that these two cryptocurrencies can be ideal for financial diversification. Bouri et al. (2020) compared the safe-haven roles of Bitcoin, commodities, and gold against global and country stock market indices. The results indicated that Bitcoin is isolated from financial assets and can be seen as a new virtual gold. Their results are similar to that of Dyhrberg (2016a).

Previous studies concentrated mainly on Bitcoin in contrast to gold and other financial assets, while little attention was paid to other cryptocurrencies. Given that the information provided by the VIX serves as a valuable reference to investors, it is imperative to examine the relation between cryptocurrencies and the VIX. In this
paper, we analyze the relationship between the cryptocurrencies volatilities, American indices (S&P500, Nasdaq, and VIX), oil, and gold prices. First, we estimate the spillover effect between cryptocurrencies and other assets. Second, we estimate the dynamic conditional correlations between the crypto-currencies. Finally, we examine the dynamic conditional correlations between crypto-currencies, American indices, gold, and oil returns. This study adds to the existing literature in two ways. First, it investigates the relationships between cryptocurrencies and financial assets in contrast to gold, especially during the COVID-19 outbreak. Second, it analyzes the relationship between five cryptocurrencies and VIX, on the one hand, and between five cryptocurrencies and WTI on the other hand.

The layout of this paper is as follows. Section 2 gives an outline of the econometric methodology adopted. Section 3 is devoted to highlight the relevant data and the empirical findings. Finally, Sect. 4 concludes.

2 Empirical methodology

First, we used the GARCH model, developed by Bollerslev (1986), which describes the volatility of assets and cryptocurrencies. The empirical model is particularly useful in that it allows for the maintenance of conditional volatilities.

The conditional variance equation of the GARCH(1, 1) model is given by:

$$ h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} $$

For each market $i$, $\omega$ represents the constant, $h_t$ is the conditional variance, $\varepsilon_{t-1}^2$ is the unexpected past shocks (news) when $\alpha$ captures the short run persistence (the ARCH effect), and $\beta$ represents the long run persistence of past volatilities (the GARCH effect). Also, we extracted the conditional variance for American stock indices (S&P500 and Nasdaq), oil (WTI), gold price, investor sentiment (VIX), and for cryptocurrencies. Then, we estimate the following model for identifying the relationship between the volatilities American stock indices (S&P500 and Nasdaq), oil, gold, investor sentiment (VIX), and cryptocurrencies:

$$ h_t = \beta_0 + \beta_1 h_t(VIX) + \beta_2 h_t(\text{Gold}) + \beta_3 h_t(Wti) + \beta_4 h_t(\text{cryptocurrency}) $$

Second, we estimated the volatilities transmission between stock indices, oil (WTI), gold price, investor sentiment (VIX), and cryptocurrencies by using a multivariate BEKK-GARCH model.

2.1 Volatilities transmission between stock indices, assets, and cryptocurrencies

Considering the multivariate BEKK formulations of conditional variance introduced by Baba et al. (1990), the conditional variance of multivariate GARCH(1,1) model can be written as:

$$ H_t = C'C + A'\varepsilon_{t-1}^2 A + B'H_{t-1}B $$
where $H_t$ is conditional variance of the multivariate BEKK-GARCH, $C$ is equal $N \times N$ upper triangular matrix of constants, $A$ and $B$ are $N \times N$ matrices of parameters, is $\varepsilon_{t-1}$ a residual matrix at time $t-1$. In the case, the model can be written as follows:

$$H_t = M_t + A'_t \varepsilon_{t-1} \times \varepsilon_{t-1}' A_t + B'_t H_{t-1} B_t$$  \hspace{1cm} (4)$$

$M_t$, $A_t$ and $B_t$ are coefficients of the estimated BEKK-GARCH model as expressed below:

$$H_t = (h_{it}) \text{ with } i = 1, 2, \ldots, 5$$  \hspace{1cm} (5)$$

$$M_t = (C_{i,j-t}) \text{ with } i, j = 1, 2, \ldots, 5$$  \hspace{1cm} (6)$$

$$A_t = (\alpha_{ij,t}) \text{ with } i, j = 1, 2, \ldots, 5$$  \hspace{1cm} (7)$$

$$B_t = (\beta_{ij,t}) \text{ with } i, j = 1, 2, \ldots, 5$$  \hspace{1cm} (8)$$

The aim of this study is to estimate the above models and examine the nature of the volatility relationship between cryptocurrencies and American indices (S&P500, Nasdaq and VIX), oil, and gold returns. Therefore, we are interested in $\alpha_{1t}$ and $\beta_{1t}$ for studying the spillover effect.

Third, we estimate the dynamic conditional correlation between cryptocurrencies, oil, gold, and American indices (S&P500, Nasdaq, and VIX).

### 2.2 Dynamic conditional correlation

To investigate the time-varying volatilities and correlations between the cryptocurrencies and each market (American indices, oil and gold), we relied on the dynamic conditional correlation of the DCC-GARCH model introduced by Engle (2002). On the one hand, we estimated the dynamic conditional correlation between cryptocurrencies and the American indices (S&P500, Nasdaq, and VIX). On the other hand, we assessed the dynamic conditional correlation between cryptocurrencies returns ($r_{1t}$) and oil returns ($r_{2t}$). Finally, we estimated the dynamic conditional correlation between cryptocurrencies returns ($r_{1t}$) and gold returns ($r_{2t}$), by using the DCC-GARCH(1.1). Let $r_t$ be the vector composed of two returns series, $r_t = (r_{1t}, r_{2t})'$. We have:

$$A(L)r_t = \omega + \varepsilon_t$$  \hspace{1cm} (9)$$

where $A(L)$ is the lag polynomial and $\varepsilon_t$ is the error-term vector.

The DCC model is based on the hypothesis that the conditional returns are normally distributed with zero mean and conditional covariance matrix $H_t = E[r_t r_t']$ expressed as follows:

$$H = D_t R_t D_t$$  \hspace{1cm} (10)$$
where $D_t = \left[ \text{diag} \left( h_t \right) \right]^{1/2}$ is the diagonal matrix of conditional variance and its elements are generated using a univariate GARCH(1,1) process from Eq. (1).

$R_t$ is the conditional correlation matrix of the standardized returns $\varepsilon_t$ with $\varepsilon_t = D_t^{-1} r_t$.

$$R_t = \begin{bmatrix} 1 & q_{12t} \\ q_{21t} & 1 \end{bmatrix}$$  \quad (11)

The matrix $R_t$ is decomposed into:

$$R_t = Q_t^{-1} Q_t Q_t^{-1}$$  \quad (12)

where $Q_t$ is the positive definite matrix containing the conditional variances–covariances of $\varepsilon_t$, and $Q_t^{-1}$ is the inverted diagonal matrix with the square root of the diagonal elements of $Q_t$:

$$Q_t^{-1} = \begin{bmatrix} 1/\sqrt{q_{11t}} & 0 \\ 0 & 1/\sqrt{q_{22t}} \end{bmatrix}$$  \quad (13)

The DCC(1,1) model is then given by:

$$Q_t = \omega + \alpha \varepsilon_{t-1} \varepsilon_{t-1}' + \beta Q_{t-1}$$  \quad (14)

where $\omega = (1 - \alpha - \beta) \tilde{Q}$. Following Engle (2002), $\tilde{Q}$ is treated as the second moment of $\varepsilon_t$ and is proxied by the sample moment of the estimated returns in large systems.

In this paper, the key element of interest in $R_t$ is

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t} q_{22,t}}}$$  \quad (15)

which represents the conditional correlation between cryptocurrencies, stock indices, VIX, oil, and gold price.

3 Data and results

3.1 Data and descriptive statistics

Adjusted closing-price data relevant to five popular cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple), American indices (S&P500, Nasdaq, and VIX), oil (WTI) prices, and gold prices are applied in this study. The database was collected from the CoinMarketCap, Datastream, and ABC bourse, regarding the period ranging from 01/01/2016 to 01/04/2020 on a daily frequency basis, making up a total of 1098 observations. We used Oxmetrics software.1 The entire market data on close of day prices are synchronized to eliminate non-trading days, and daily returns are defined

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1 Source: https://www.timberlake.co.uk/software/oxmetrics.html.
Table 1 presents the Descriptive Statistics of assets and cryptocurrencies returns and the estimation results of GARCH(1,1) model.

Table 1 presents a statistic summary of American indices returns (S&P500, Nasdaq, VIX), oil, gold, and cryptocurrencies returns. All assets recorded mean positive returns during this period, except for the oil returns, whereas for assets, gold presents the lowest risk and for cryptocurrencies, and Bitcoin presents the lowest risk. On the contrary, the oil returns present the highest risk and for cryptocurrencies, the Monero present the highest risk. It is noted that the gold market recorded the best risk-return and it is considered a safe haven for investors.

All markets returns (cryptocurrencies and financial assets) have kurtosis values higher than three and the distribution of returns is negatively and positively skewed for

by $rt = \ln(pt/pt-1)$, with $pt$ standing for the series respective closing price on day $t$. Table 1 present the Descriptive Statistics of assets and cryptocurrencies returns and the estimation results of GARCH(1,1) model.
Panel 1: Conditional volatilities of cryptocurrencies

Fig. 1 Conditional volatilities of assets and cryptocurrencies

all-time assets, which indicates that all return markets are far from normally distributed. Therefore, the assumption of Gaussian returns is rejected by the Jarque-Bera test for all assets and cryptocurrencies. The empirical statistics of the Engle (1982) test for conditional heteroskedasticity are significant for all cases suggesting the presence of ARCH effects in returns which justifying our choice of GARCH models.

Figure 1, below, illustrates the volatilities of each asset (S&P500, Nasdaq, VIX, WTI, and gold) extracting by the model GARCH(1,1).

By looking at Fig. 1 (panel 1), we can observe that in general cryptocurrency returns present higher volatility than the conventional asset class returns (panel 2). In addition, the Ripple records the highest conditional volatility among the studied cryptocurrencies. Figure 1 identifies high volatility during the 2017 year especially with the launch of Bitcoin futures. However, it can be seen that the five cryptocurrencies
present almost identical volatility movements. This result is similar to that of Beneki et al. (2019). Early in the first quarter of 2020, the cryptocurrency prices experienced enormous volatility. Indeed, the price of benchmark crypto reached $10,482, a new high in this quarter. A month after the increase, a plunge in the cryptocurrency prices suddenly swept the entire market. The Bitcoin price fell dramatically, reaching a low of $3869.5. After that, the price rebounded to about $6000. The prices of other cryptocurrencies recorded the same pace.

Figure 1 shows high volatilities of American indices (S&P500, Nasdaq, and VIX) during the 2017/2018 period. In fact, stocks literally fell off a cliff and investors couldn’t sell stocks fast enough. Because, investors didn’t see a resolution to the US–China trade war and the downturn in the economy. Add in the complete mistrust of the Federal Reserve policy. In contrast, we show a low level of oil and volatilities. The declining US dollar and rising inflationary pressures continue to provide favorable
tailwinds for gold. Except, during the first months of 2016, crude oil prices were relatively more volatile. This elevated volatility occurred, when overall oil prices were low, by high uncertainty related to supply, demand, and inventories. During the first quarter of 2020, the US stock market experienced enormous volatility as the coronavirus pandemic developed throughout late February and March. US stock markets witnessed one of their worst quarters. In addition, the economic conflict between Russia and Saudi Arabia resulted in a sheer drop in the oil prices over the spring of 2020.

4 Results

The estimated results of Eq. (2) analyze the relation between the conditional volatility of the US indices (SP&500 and NASDAQ) and the conditional volatility of VIX, GOLD, WTI, and cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple) and are, respectively, reported in Table 2. We show a high level of adjusted R-squared which indicates that the regression model is well suited to the data and it is well estimated. From Table 2, we find that the conditional volatility of VIX has a positive and significant effect on the conditional volatility of US indices (SP&500 and NASDAQ) in all regressions. However, the coefficient is low. It indicates that the conditional volatility of the VIX does not have a big impact on the conditional volatility of the US indices. The results suggest also that there is a significant and positive relationship between the conditional volatility of WTI and those of the US indices. On average, every 1% increase of the conditional volatility of WTI contributes to almost 0.1635% increase of the conditional volatility of SP 500 and almost 0.2454% increase of the conditional volatility of NASDAQ. This supports the findings of Klein et al. (2018). The results reveal a significant and negative relationship (at the 0.01 level) between the conditional volatilities of GOLD and that of the US indices. On average, every 1% increase of the conditional volatility of GOLD contributes to almost 0.8036% decrease of the conditional volatility of S&P500 and almost 0.6951% decrease of the conditional volatility of NASDAQ. By applying the categorizations of Baur and Lucey (2010), we predict that the subsequent results will confirm the idea that gold is a hedge. With regard to cryptocurrencies, we find that the conditional volatilities of Bitcoin, Dash, and Monero have a positive and significant effect on the conditional volatility of the US indices (SP&500 and NASDAQ). However, the coefficient is low. It indicates that the conditional volatility of cryptocurrencies has a low affect on the conditional volatility of the US indices.

In Eq. 4, the diagonal parameters in matrix A, $\alpha_{1i}$, capture a ARCH effects from variable $l$ to assets $i$ while the diagonal parameters in matrix B, $\beta_{1j}$ capture a GARCH effects from variable $l$ to assets $j$.

In Table 3, the results of estimating the ARCH ($\alpha_{1l}$) parameters show evidence of bi-directional shock transmission effects between Bitcoin and each cryptocurrency (Dash, Ethereum, Monero, and Ripple), since the off-diagonal parameters ($\alpha_{12}$, $\alpha_{13}$, $\alpha_{14}$ and $\alpha_{15}$) are all statistically significant. It should be noticed, though, that for the pair Bitcoin- cryptocurrencies, $\alpha_{1l}$ is significantly positive. Consequently, the past
Table 2 Correlation between conditional volatilities of US indices, assets, and cryptocurrencies

|                | Bitcoin | Dash   | Ethereum | Monero | Ripple | Bitcoin | Dash   | Ethereum | Monero | Ripple |
|----------------|---------|--------|----------|--------|--------|---------|--------|----------|--------|--------|
| Conditional volatility of SP 500 |         |        |          |        |        |         |        |          |        |        |
| $\beta_0$      | 0.0004* | 0.0002*| 0.0001*  | 0.0003 | 0.0002*| 0.0002* | 0.0003*| 0.0002*  | 0.0001*| 0.0003*|
|                 | (4.939) | (7.562)| (7.387)  | (8.592)| (7.823)| (10.925)| (12.902)| (14.872) | (15.781)| (15.256)|
| $\beta_1$      | 0.0062* | 0.0061*| 0.0059*  | 0.0058*| 0.0063*| 0.0064* | 0.0068* | 0.0062*  | 0.0061*| 0.0059*|
|                 | (15.496)| (18.356)| (19.331)| (19.828)| (15.971)| (11.607)| (13.141)| (14.054) | (12.828)| (14.983)|
| $\beta_2$      | −0.9279*| −0.5525*| −0.7625*| −0.8439*| −0.9312*| −0.6201*| −0.7264*| −0.7428* | −0.6948*| −0.6914*|
|                 | (−11.493)| (−12.089)| (−11.072)| (−12.961)| (−12.513)| (−14.986)| (−14.544)| (−18.296)| (−18.461)| (−19.502)|
| $\beta_3$      | 0.1712* | 0.1530*| 0.1627*  | 0.1682*| 0.1625*| 0.1918* | 0.2547* | 0.2598*  | 0.2678*| 0.2531*|
|                 | (19.534)| (15.995)| (15.909)| (18.157)| (18.381)| (18.958)| (19.859)| (19.336) | (20.872)| (20.071)|
| $\beta_4$      | 0.0091* | 0.0014*| 0.0007   | −0.0013*| −0.0002| 0.0061* | 0.0017* | 0.0009*  | −0.0031*| −0.006***|
|                 | (5.718) | (8.849)| (1.232)  | (−3.892)| (−0.717)| (6.726) | (5.415) | (3.492)  | (−5.959)| (−1.963)|
| $R^2$          | 0.6305  | 0.6252  | 0.6153   | 0.6202  | 0.6146 | 0.6083  | 0.6066  | 0.6989   | 0.6096 | 0.6006 |
| Adjusted $R^2$ | 0.6375  | 0.6262  | 0.6183   | 0.6272  | 0.6216 | 0.6153  | 0.6136  | 0.7058   | 0.6106 | 0.6105 |

This table reports the results of the ordinary least squares (OLS) method. $\beta_0$, $\beta_1$, $\beta_2$, $\beta_3$ and $\beta_4$ are the estimation parameters of Eq. 2. *Significant at the 1% level, **Significant at the 5% level, ***Significant at the 10% level.
news about shocks in Bitcoin positively affects the current conditional volatility of cryptocurrencies. The same results are found for Dash, Ethereum, Monero, and Ripple.

The estimation of the GARCH ($\beta_1$) parameters is significantly positive between Bitcoin and each cryptocurrency (Dash, Ethereum, Monero, and Ripple). Consequently, the current conditional volatility of Bitcoin depends not only on its own past volatility but also on past volatility of the other cryptocurrencies (Dash, Ethereum, Monero, and Ripple), suggesting the interdependence between them.

For Dash, Ethereum, Monero, Ripple, $\beta_1$ is positive for both pairs of cryptocurrencies suggesting that the current conditional volatility of one cryptocurrency depends not only on its own past volatility but also positively on past volatility of the other cryptocurrency, suggesting interlinkages between them. On the other hand, the significant and positive $\beta_{12}$, $\beta_{13}$, $\beta_{14}$ and $\beta_{15}$ parameters estimated indicate bi-directional positive volatility linkages between all cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple), which further confirm interdependencies within the cryptocurrency market. Our findings thus support the studies of Fry and Cheah (2016), Ciaian et al. (2018), Corbet et al. (2018), and Katsiampa (2019a, 2019b) on interdependencies within the cryptocurrency market.

In Tables 4 and 5, the results of estimating the ARCH ($\alpha_1$) parameters show evidence of shock transmission effects between each American index (S&P500, Nasdaq) and all cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple). It should be noticed, though, that for the pair American index-cryptocurrencies, $\alpha_1$ is significantly positive. Consequently, the past news about shocks in American indexes (S&P500, Nasdaq) positively affects the current conditional volatility of cryptocurrencies. For ARCH parameters ($\alpha_{12}$, $\alpha_{13}$ and $\alpha_{14}$), we find the same results between American index-oil, American index-VIX, and American index-gold, suggesting the shock transmission of American indexes volatilities to oil, VIX, and gold returns.

For American indexes (S&P500, Nasdaq), the estimation of GARCH ($\beta_{12}$, $\beta_{13}$, $\beta_{14}$) parameters is significantly positive between American indexes-oil, American indexes-VIX, and American indexes-gold, respectively. So, for oil, gold, and VIX, the current conditional volatility depends not only on its own past volatility but also on past volatilities of the American indexes.

The estimation of GARCH ($\beta_{15}$) parameters is significantly positive between American indexes and each cryptocurrency (Dash, Ethereum, Monero, and Ripple) except for Bitcoin is significantly negative. Consequently, the current conditional volatility of each cryptocurrency depends not only on its own past volatility but also on past volatilities of the American indexes.

Recap, the results of Tables 4 and 5 find a spillover effect from American indexes (S&P500, Nasdaq) volatilities to oil, VIX, gold, and cryptocurrencies.

From Table 6, the results of estimating the ARCH ($\alpha_{15}$ and $\alpha_{13}$) parameters show evidence of shock transmission effects from oil to cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple) and from oil to gold. It should be noticed, though, that for the pair oil-cryptocurrencies and the pair oil-gold, ($\alpha_{15}$ and $\alpha_{13}$) are significantly positive. Consequently, the past news about shocks in oil volatilities positively affects the current conditional volatility of the cryptocurrencies and gold. On the contrary, the estimation of ARCH ($\alpha_{12}$ and $\alpha_{14}$) parameters is significantly negative from oil to VIX and stock index (S&P500) returns. Consequently, the past news about shocks in
Table 3 BEKK model parameter estimates between cryptocurrencies

| Parameters/vecteur | Bitcoin, Dash, Ethereum, Monero, Ripple | Dash, Bitcoin, Ethereum, Monero, Ripple | Ethereum, Dash, Bitcoin, Monero, Ripple | Monero Bitcoin, Dash, Ethereum, Ripple | Ripple, Bitcoin, Dash, Ethereum, Ripple, Monero |
|--------------------|----------------------------------------|----------------------------------------|----------------------------------------|----------------------------------------|-----------------------------------------------|
| **Variance decomposition** | | | | | |
| \( \alpha_{1,1} \) | 0.4763* | 0.2991* | 0.6161 | 0.6653* | 0.8731* |
| (5.474) | (7.388) | (1.014) | (5.308) | (7.884) | |
| \( \alpha_{1,2} \) | 0.4476* | 0.3088* | 0.4366* | 0.4909* | 0.4930* |
| (6.848) | (13.69) | (6.53) | (7.538) | (7.821) | |
| \( \alpha_{1,3} \) | 0.5563* | 0.2815* | 0.5141* | 0.4027* | 0.3872* |
| (8.931) | (10.48) | (7.808) | (8.033) | (7.434) | |
| \( \alpha_{1,4} \) | 0.3885* | 0.2773* | 0.3617** | 0.3417* | 0.3344* |
| (7.59) | (6.141) | (2.516) | (8.457) | (2.966) | |
| \( \alpha_{1,5} \) | 0.4198* | 0.3127* | 0.4327* | 0.3896* | 0.3300* |
| (5.461) | (9.252) | (4.389) | (10.28) | (4.363) | |
| \( \beta_{1,1} \) | 0.9451* | 0.9405* | 0.8271* | 0.6061* | 0.4785* |
| (122.1) | (67.49) | (9.35) | (4.878) | (4.363) | |
| \( \beta_{1,2} \) | 0.8823* | 0.9511* | 0.8818* | 0.8637* | 0.8686* |
| (46.48) | (151.3) | (44.81) | (25.90) | (37.22) | |
| \( \beta_{1,3} \) | 0.6097* | 0.9577* | 0.7813* | 0.9153* | 0.9219* |
| (3.023) | (132.8) | (27.54) | (41.29) | (48.96) | |
| \( \beta_{1,4} \) | 0.9116* | 0.9554* | 0.9316* | 0.9397* | 0.9424* |
| (36.49) | (68.61) | (14.21) | (55.95) | (44.29) | |
| \( \beta_{1,5} \) | 0.9064* | 0.9418* | 0.8986* | 0.9209* | 0.9439* |
| (31.08) | (91.24) | (12.51) | (39.33) | (46.65) | |
| Log Likelihood | 9055.3 | 9291.7 | 9072.3 | 9061.9 | 9008.2 |

Significant at: *1, **5, and ***10 percent levels; \( t \) values given in parentheses; the results of estimated mean equation and constants of each variance in Eq. (4) are not reported for the sake of brevity.
Table 4 BEKK model parameter estimates vector (S&P500, WTI, gold, VIX, cryptocurrency)

|                | Bitcoin | Dash    | Ethereum | Monero | Ripple |
|----------------|---------|---------|----------|--------|--------|
| $\alpha_{1,1}$ | 0.6269  | 0.4763* | 0.4118*  | 0.4855* | 0.4694* |
|                | (0.7903)| (8.732) | (8.841)  | (13.94)| (13.82)|
| $\alpha_{1,2}$ | 0.5275  | 0.2970* | 0.1971*  | 0.2959* | 0.2966* |
|                | (5.235)*| (4.988) | (7.29)   | (4.105)| (3.832)|
| $\alpha_{1,3}$ | 0.0016* | 0.1083* | 0.1275*  | 0.1570* | 0.1513* |
|                | (5.708) | (4.889) | (5.704)  | (7.231)| (7.697)|
| $\alpha_{1,4}$ | 0.3513  | 0.3546* | 0.3543*  | 0.4081* | 0.4017* |
|                | (4.324)*| (5.437) | (5.446)  | (8.494)| (7.966)|
| $\alpha_{1,5}$ | 0.4928  | 0.2897* | 0.4047*  | 0.2906* | 0.4823* |
|                | (4.053)*| (3.452) | (6.718)  | (3.241)| (5.42) |
| $\beta_{1,1}$  | 0.8996  | 0.8673* | 0.8754*  | 0.8741* | 0.8829* |
|                | (51.71)*| (33.58) | (46.54)  | (66.16)| (73.65)|
| $\beta_{1,2}$  | 0.4507  | 0.9451* | 0.9453*  | 0.9552* | 0.9549* |
|                | (4.943)*| (48.55) | (32.66)  | (84.29)| (76.11)|
| $\beta_{1,3}$  | 0.0774* | 0.9918* | 0.9795*  | 0.9813* | 0.9818* |
|                | (5.403) | (171.6) | (101.4)  | (336.3)| (373.0)|
| $\beta_{1,4}$  | 0.9223  | 0.8897* | 0.8967*  | 0.8842* | 0.8909* |
|                | (48.95)*| (23.57) | (34.16)  | (53.54)| (56.70)|
| $\beta_{1,5}$  | −0.8177*| 0.9398* | 0.7077*  | 0.7949* | 0.7043* |
|                | (−24.15)| (25.34) | (3.370)  | (24.30)| (15.31)|
| Log Likelihood | 10815.2 | 13201.3 | 13147.9  | 12996.3| 13101.3|

Significant at: *1, * *5, and * * *10 percent levels; $t$ values given in parentheses; the results of estimated mean equation and constants of each variance in Eq. (4) are not reported for the sake of brevity.

Oil negatively affects the current conditional volatilities of stock index and American investors’ sentiment.

The estimation of GARCH ($\beta_{15}$) parameters is significantly positive between oil returns and cryptocurrencies. Consequently, the current conditional volatility of each cryptocurrency depends not only on its own past volatility but also on past volatilities of the oil market.

From Table 6, the estimation of GARCH ($\beta_{12}, \beta_{13}, \beta_{14}$) parameters is significantly positive between oil, American index, investor sentiment (VIX), and gold returns. Consequently, the current conditional volatilities of the stock market, gold, and investors’ sentiment depend not only on their own past volatility but also on past volatilities of the oil market.

So, the results of Table 6 prove the spillover effect of oil volatility on financial assets (stock indexes and gold) and on cryptocurrencies.

From Table 7, the results of estimating the ARCH ($\alpha_{15}$) parameters show evidence of shock transmission effects from gold to cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple). It should be noticed that for the pair gold–cryptocurrencies, $\alpha_{15}$ is significantly positive. Consequently, the past news about shocks in gold returns positively affects the current conditional volatility of cryptocurrencies. On the contrary,
the estimation of ARCH ($\alpha_{12}$, $\alpha_{13}$ and $\alpha_{14}$) parameters is significantly negative from gold to VIX, stock index (S&P500), and oil returns. Consequently, the past news about shocks in gold negatively affects the current conditional volatilities of the stock index, investors’ sentiment, and oil.

Also, the estimation of GARCH ($\beta_{12}$, $\beta_{13}$, $\beta_{14}$, and $\beta_{15}$) parameters is significantly positive from the volatility of the gold to the volatilities of American index, oil price, cryptocurrencies, and investor sentiment (VIX). Consequently, the current conditional volatilities of the stock market, oil, cryptocurrencies, and investor sentiment depends not only on their own past volatility but also on past volatilities of the gold price. So, the results of Table 7 prove a spillover effect of gold volatility on financial assets and on cryptocurrencies.

From Table 8, the results of estimating the ARCH ($\alpha_{15}$ and $\alpha_{14}$) parameters show evidence of shock transmission effects from VIX to cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple) and gold. It should be noticed that for the pair VIX-cryptocurrencies and the pair VIX- gold, ($\alpha_{15}$ and $\alpha_{14}$) are significantly positive. Consequently, the past news about shocks in VIX positively affects the current conditional volatilities of cryptocurrencies and gold. On the contrary, the estimation of ARCH ($\alpha_{12}$, $\alpha_{13}$) parameters is significantly negative between VIX and stock index.
Table 6 BEKK model parameter estimates vector (WTI, S&P500, gold, VIX, cryptocurrency)

|            | Bitcoin | Dash | Ethereum | Monero | Ripple |
|------------|---------|------|----------|--------|--------|
| $\alpha_{1,1}$ | 0.2604* | 0.2242** | 0.2706* | 0.3052* | 0.2530* |
|            | (2.82)  | (1.997) | (2.868)  | (3.443) | (2.675) |
| $\alpha_{1,2}$ | $-0.5952^*$ | $-0.5184^*$ | $-0.5285^*$ | $-0.4888^*$ | $-0.5245^*$ |
|            | ($-15.75$) | ($-9.46$) | ($-9.17$) | ($-9.267$) | ($-9.891$) |
| $\alpha_{1,3}$ | 0.0981* | 0.1359* | 0.1086* | 0.1507* | 0.1100* |
|            | (4.076)  | (2.675)  | (4.884)  | (4.129)  | (5.712)  |
| $\alpha_{1,4}$ | $-0.3715^*$ | $-0.3710^*$ | $-0.3669^*$ | $-0.3498^*$ | $-0.3591^*$ |
|            | ($-5.49$) | ($-6.011$) | ($-5.572$) | ($-5.871$) | ($-5.83$) |
| $\alpha_{1,5}$ | 0.2334* | 0.2593** | 0.1893** | 0.2270* | 0.2884* |
|            | (2.557)  | (1.977)  | (1.994)  | (3.520)  | (4.989)  |
| $\beta_{1,1}$ | 0.9654* | 0.9437* | 0.9337* | 0.9337* | 0.9500* |
|            | (46.36)  | (24.18)  | (28.62)  | (25.39)  | (28.86)  |
| $\beta_{1,2}$ | 0.7061* | 0.8550* | 0.8489* | 0.8687* | 0.8486* |
|            | (33.23)  | (27.51)  | (24.47)  | (37.13)  | (26.31)  |
| $\beta_{1,3}$ | 0.9886* | 0.9874* | 0.9912* | 0.9854* | 0.9909* |
|            | (485.7)  | (46.37)  | (292.1)  | (80.66)  | (310.2)  |
| $\beta_{1,4}$ | 0.8907* | 0.8754* | 0.8780* | 0.8909* | 0.8785* |
|            | (47.16)  | (24.66)  | (24.16)  | (28.13)  | (24.65)  |
| $\beta_{1,5}$ | 0.3100*** | 0.9515* | 0.9625* | 0.9401* | 0.9342* |
|            | (1.938)  | (16.69)  | (36.64)  | (52.99)  | (39.56)  |
| Log likelihood | 13442.6 | 13102.7 | 13014.8 | 13008.4 | 13086.7 |

Significant at: *1%, * *5%, and * * *10 percent levels; $t$ values given in parentheses; the results of estimated mean equation and constants of each variance in Eq. (4) are not reported for the sake of brevity.

(S&P500) and, respectively, between VIX and oil returns. Consequently, the past news about shocks in investors’ sentiment negatively affects the current conditional volatilities of the stock index and oil.

The estimation of GARCH ($\beta_{12}$, $\beta_{13}$, $\beta_{14}$ and $\beta_{15}$) parameters is significant between VIX, oil, American index, cryptocurrencies, and gold returns. Consequently, the current conditional volatilities of the stock market, oil, cryptocurrencies, and gold depend not only on its own past volatility but also on past volatilities of the American investors’ sentiment.

Consequently, for the ARCH ($\alpha_{12}$, $\alpha_{13}$, $\alpha_{14}$ and $\alpha_{15}$) and GARCH ($\beta_{12}$, $\beta_{13}$, $\beta_{14}$ and $\beta_{15}$) parameters, the results identify the shock and volatilities transmission of investors’ sentiment to the stock market, gold, oil, and cryptocurrencies volatilities. So, the results of Table 8 indicate a spillover effect of the pessimism sentiment of American investors on stock, gold, oil, and cryptocurrency markets during higher volatility (coronavirus crisis).

From Table 9, the results of estimating the ARCH ($\alpha_{12}$, $\alpha_{13}$, $\alpha_{14}$ and $\alpha_{15}$) parameters show evidence of shock transmission effects from cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple) to American stock index (S&P500), oil, investors’ sentiment (VIX), and gold.
The estimation of ARCH ($\alpha_{12}$, $\alpha_{13}$, and $\alpha_{15}$) parameters is significantly positive from cryptocurrencies to S&P500, oil, and gold returns, except for Bitcoin. So, the past news about shocks in cryptocurrencies (Dash, Ethereum, Monero, and Ripple) positively affects the current conditional volatilities of the stock index, oil, and gold returns. On the contrary, the estimation of ARCH ($\alpha_{14}$) parameters is significantly negative between cryptocurrencies and VIX. Consequently, the past news about shocks in cryptocurrencies negatively affects the current conditional volatilities of investors’ sentiment.

Also, the estimation of GARCH ($\beta_{12}$, $\beta_{13}$, and $\beta_{15}$) parameters is significantly positive between cryptocurrencies, VIX, oil, and American index returns. Consequently, the current conditional volatilities of the stock market, investors’ sentiment, and oil depend not only on their own past volatility but also on past volatilities of the cryptocurrencies. The estimation of GARCH ($\beta_{14}$) parameters is significantly negative between cryptocurrencies and gold. Consequently, the current conditional volatility of the gold depends not only on its own past volatility but also on past volatilities of the cryptocurrencies. So, the results of Table 9 indicate a spillover effect of cryptocurrencies volatilities on financial assets (stock index, gold, and oil) and on American investors’ sentiment.
Recap, the estimation results of Eq. (4) of the BEKK-GARCH(1.1) model prove the bidirectional volatility spillover between cryptocurrencies, stock indexes, oil, and gold markets.

The dynamic conditional correlations by estimating Eq. 15 of the DCC-GARCH(1.1) model are presented in Figs. 2, 3, 4, 5, 6. Based on the DCC-GARCH framework, firstly, we estimated the dynamic conditional correlations between Bitcoin and the other cryptocurrencies considered. Secondly, we focused on the time-varying conditional correlation between Bitcoin and the other conventional asset classes (oil, gold, and stock indexes). When focusing on the time-varying conditional correlation between Bitcoin and the other cryptocurrencies in Fig. 2, we can identify significant changes between negative and positive values before the second half of 2017. However, since the end of 2017, there is a significant persistence of correlation in high positive values. More specifically, this correlation between cryptocurrencies exhibits positive values during the period that presented a fast pace of prices increases. Nevertheless, when prices of cryptocurrencies decreased significantly by the beginning of 2018, the correlation remains positive and reached higher levels than before.

result is consistent with that of Aslanidis et al. (2019). At the beginning of 2020, we show that the correlation increased between Bitcoin and cryptocurrencies. This is the consequence of the coronavirus effect on cryptocurrencies.

Table 9 BEKK model parameter estimates vector (cryptocurrency, S&P500, WTI, gold, VIX)

|                     | Bitcoin | Dash   | Ethereum | Monero | Ripple |
|---------------------|---------|--------|----------|--------|--------|
| Variance decomposition |         |        |          |        |        |
| $\alpha_{1,1}$     | 0.2084** | 0.2966* | 0.4047*  | 0.2235* | 0.2815* |
|         (2.514)    | (6.743) | (3.562) | (5.114)  |        |        |
| $\alpha_{1,2}$     | −0.4931* | 0.4964* | 0.4573*  | 0.4718* | 0.4862* |
|         (−9.461)   | (9.948) | (9.628) | (10.10)  |        |        |
| $\alpha_{1,3}$     | −0.2999* | 0.2934* | 0.3048*  | 0.2951* | 0.2820* |
|         (−4.531)   | (4.883) | (5.109) | (4.884)  |        |        |
| $\alpha_{1,4}$     | −0.1542* | −0.1294* | −0.1325* | −0.1141* | −0.1354* |
|         (−5.283)   | (−5.381) | (−5.693) | (−2.358) |        |        |
| $\alpha_{1,5}$     | −0.3656* | 0.3689* | 0.3396*  | 0.3505* | 0.3552* |
|         (−5.607)   | (5.669) | (6.002) | (5.68)   |        |        |
| $\beta_{1,1}$      | 0.9566* | 0.9384* | 0.7186*  | 0.9453* | 0.9402* |
|         (37.01)    | (15.86) | (46.62) | (48.20)  |        |        |
| $\beta_{1,2}$      | 0.8659* | 0.8615* | 0.8774*  | 0.8723* | 0.8625* |
|         (36.35)    | (35.43) | (43.53) | (41.80)  |        |        |
| $\beta_{1,3}$      | 0.9431* | 0.9480* | 0.9443*  | 0.9467* | 0.9494* |
|         (38.96)    | (50.04) | (46.49) | (47.09)  |        |        |
| $\beta_{1,4}$      | −0.9822* | −0.9887* | −0.5518* | −0.3121* | −0.9874* |
|         (−89.13)   | (−32.97) | (112.7) | (139.5)  |        |        |
| $\beta_{1,5}$      | 0.8865* | 0.8732* | 0.9005*  | 0.8927* | 0.8810* |
|         (23.99)    | (21.75) | (30.44) | (25.87)  |        |        |
| Log likelihood     | 13646.4 | 13247.7 | 13127.5  | 13048.6 | 13214.7 |

Significant at: *1, * *5, and * * *10 percent levels; t values given in parentheses; the results of estimated mean equation and constants of each variance in Eq. (4) are not reported for the sake of brevity.
NASDAQ. In fact, we can consider the studied cryptocurrencies except for Bitcoin as diversifier assets for the SP&500. Rounding up the analysis, we will compare the conditional correlations of gold and cryptocurrencies with SP&500 and NASDAQ, before the coronavirus crisis. We show that the correlation between gold and US indices is negative in the mean. Based on this result and applying the categorizations of Baur and Lucey (2010), we consider that gold is a Hedge. This result is consistent with that of Klein et al. (2018), Charfeddine et al. (2020), and Bouri et al. (2020). Although the correlation between gold and US indices is negative in mean, it is positive during the fourth quarter of 2017. This can, firstly, be due to the spectacular rise of the US indices driven by a series of strong economic reports from across the globe and expectations for strong fourth-quarter earnings. Secondly, at the end of 2017, Bitcoin’s price was skyrocketing with the launch of Bitcoin futures. At the beginning of 2020, we observe that the correlation increased between cryptocurrencies and American markets which confirm the contagion effect of coronavirus between them. Contrary to gold, digital assets aren’t a safe haven for US investors during the coronavirus crisis.

Figure 4 shows the time-varying correlations of cryptocurrencies and VIX. We observe that the dynamic correlations for the couples Ripple-VIX, Monero-VIX, and Ethereum-VIX are extremely volatile and alternating between positive and negative values. However, we note that correlations become negative and weak for the couples Bitcoin-VIX and Dash-VIX. This result is consistent with that of Jareno et al. (2020). In 2018, we show that the correlations decreased following the high volatility of the VIX (the highest increase in its history, it has taken more than 100% increase). Also, at the beginning of 2020, we note that correlations decreased between the VIX and cryptocurrencies following the consequence of the coronavirus. This, explain that
when the feeling of fear increases in the American market, investors turned to other assets among them the cryptocurrencies.

From Fig. 5, the study of the correlation between cryptocurrencies except for Ethereum and WTI has shown that the correlation is positive in general with a few negative spikes in the smoothed path. Non-smoothed values peak up to 0.4 and get as low as $-0.15$. The dynamic correlations between Ethereum and WTI register significant changes between negative and positive values. It spreads between 0.4 and $-0.35$.

Figure 6 shows the dynamic conditional correlations between cryptocurrencies and gold. We observe that Ethereum is the most correlated cryptocurrency with gold. The correlation is positive in general with a few negative spikes in the smoothed path. The correlation between gold and Bitcoin is positive before the second half of 2017. It becomes negative until the first half of 2018 and then becomes positive again. Nevertheless, when prices of Bitcoin increased significantly during the second half of
2017 and decreased significantly by the beginning of 2018, the correlation remains negative. At the beginning of 2020, we observe that the correlation increased between cryptocurrencies and oil which confirm the contagion effect of coronavirus between them.

When the prices of Bitcoin rose from $1000 at the beginning of 2017 to over $19,000 by mid-December, market rumors were that Bitcoin was usurping the role of gold as a store of value and an alternative to fiat currencies. Despite rising geopolitical worries, Bitcoin’s price was skyrocketing, while yellow metal’s price was languishing, staying mostly in the $1200 an ounce range. The inverse relationship between these two assets is likely added to the speculation that Bitcoin was sapping demand from the gold. When Bitcoin prices were higher, it may have reduced demand for the yellow metal. Retail investors tend to have a shorter investment horizon when Bitcoin recording parabolic increases. After this vertiginous ascent, the biggest digital coin lost

Fig. 4 Dynamic correlations between cryptocurrencies and VIX
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nearly three quarters in his value. In fact, the cryptocurrency landscape has changed. Mom-and-pop investors who drove the skyrocketing rise of Bitcoin have been pushed aside by government bans on trading. They are replaced by cryptocurrency funds, established financial firms, and wealthy individuals. Throughout 2018, Bitcoin’s price plunged and closed the year at around $4000. In the first half of 2019, Bitcoin is back. It triggered the threshold of $14,000 in June. At the beginning of 2020, we observe that the correlation increased between cryptocurrencies and gold which confirm the contagion effect of coronavirus between them.

Figure 6 concludes that the dynamic conditional correlations between Bitcoin and gold are not stable. The correlation is characterized by positive and negative spikes with no general tendency since the second half of 2018. Beyond that, it tends to increase and become positive. We assume that Bitcoin is believed to be similar to gold because this correlation is in the process to be positive and stable. This result is not similar to that in Klein et al. (2018).
5 Conclusion

Using data relevant to five popular cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, and Ripple), American indices (S&P500, Nasdaq, and VIX), oil price (WTI), and gold price, we have investigated the relationship between volatilities of cryptocurrencies and other financial assets. The results of the multivariate BEKK-GARCH(1,1) model, firstly, show higher volatility spillover between cryptocurrencies, that confirm interdependencies within the cryptocurrency market. Secondly, the results show lower volatility spillover between cryptocurrencies and financial assets. Also, the results of the BEKK-GARCH(1,1) model proved the bidirectional volatility spillover between cryptocurrencies, stock indexes, oil, and gold markets. Thirdly, it was found that the...
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current conditional volatilities of stock indices (S&P500, Nasdaq, and VIX), gold, and oil depend not only on their own past volatility but also on past volatilities of the cryptocurrencies.

When estimating the dynamic conditional correlations, we find, firstly, that Bitcoin and gold are considered as a hedge for the US investors, during stability period (before the coronavirus crisis), by applying the categorizations of Baur and Lucey (2010). Secondly, there is a significant persistence of correlation between cryptocurrencies in high positive values since the initiation of Bitcoin futures by the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) at the end of 2017. Thirdly, we have observed that the dynamic correlations for the couples Ripple-VIX, Monero-VIX, and Ethereum-VIX are extremely volatile and alternating between positive and negative values. However, we note that correlations become negative and weak for the couples Bitcoin-VIX and Dash-VIX. Fourthly, the study of the correlation between cryptocurrencies except for Ethereum and the WTI has shown that the correlation is positive in general. This explains the creation of a new cryptocurrency indexed on oil named “Bilur.”

During the stability period, our results support the position that cryptocurrency markets are a new investment asset class since they have low dynamic conditional correlations with financial assets. But, at the beginning of 2020, we observe that the correlation increased between cryptocurrencies, American indexes, and oil which confirm the contagion effect of coronavirus between them. Contrary to gold, digital assets aren’t a safe haven for US investors during the coronavirus crisis.

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