A New Evidence of the Relationship between Cryptocurrencies and other Assets from the COVID-19 Crisis[1]

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Abstract

The purpose of this paper is to reinvestigate the properties of cryptocurrencies in the COVID-19 crisis as well as their co-movements with different asset classes including different stock markets, bonds, real estate, gold and oil. To capture the change in correlation caused by crisis, we employ multivariate GARCH Dynamic Conditional Correlation model. The findings suggest that cryptocurrencies can be seen no more than a diversifier for most of the assets. For real estate and S&P500 it is confirmed to be a weak hedge, while positive and upward sloping dynamic conditional correlations with gold obtained in COVID-19 period needs to be further investigated.

Keywords: *COVID-19, cryptocurrencies, CRIX, MGARCH-DCC, conditional correlations*

JEL Classification: G11, G15, C13, C58

DOI: https://doi.org/10.31577/ekoncas.2022.07-8.03

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[1] This work is supported by the Croatian Science Foundation (CSF) under Grant [IP-2019-04 – 7816].

Author contributions: Z. Aljinović proposed the research within the CSF Project *Challenges of Alternative Investments* where she is the principal investigator. T. Šestanović was responsible for data collection. B. Škrabić-Perić and T. Šestanović proposed and described the appropriate MGARCH-DCC methodology, estimated the model in STATA and analysed the results. All authors together discussed the issue of the paper, collected and analysed theoretical framework for the research and synthetized the results and conclusions.

Disclosure statement: Authors declare that they do not have any competing financial, professional, or personal interests from other parties.

Introduction

From the moment of their emergence, as a by-product of Satoshi Nakamoto's "Peer-to-Peer Electronic Cash System" (Nakamoto, 2008), cryptocurrencies attract a lot of attention from different points of view. Especially, investors are seeking for a new investment asset. Fortunately, over the last few years, we are witnessing a real surge in academic world producing an enviable number of papers confirming the (non)existence of some favourable features of cryptocurrencies. If the definition of a particular asset class of investments as a set of investments with common risk-return characteristics and very similar reactions to economic and market events, and consequently a low correlation of returns with other classes is employed, as given in Kitces (2012), it can be said that there is a clear situation of cryptocurrencies as the evident new investment class. A sequence of research has proven the cryptocurrencies' capacity as an investment asset class (Burniske and White, 2017; Ankenbrand and Bieri, 2018; Elendner et al., 2018; Liu and Tsyvinski, 2018; Sajter, 2019; Stenså̊s et al., 2019; Gil-Alana et al., 2020). In accordance with those results, a numerous studies considered the contribution of particular cryptocurrencies, mostly Bitcoin, to portfolios with different traditional and/or alternative investments (Kajtazi and Moro, 2019; Symitsi and Chalvatzis, 2019; Platanakis and Urquhart, 2020; Li et al., 2021). Additionally, some of the research considered the contribution through a set of cryptocurrencies, mostly represented by the CRyptocurrency IndeX (CRIX) or its subsets, regarding certain criterion like market capitalization (Lee et al., 2018; Krückeberg and Scholz, 2019; Trimborn et al., 2019; Petukhina et al., 2020; Ma et al., 2020). Therefore, a unique conclusion of a contribution of cryptocurrencies in terms of Markowitz diversification, i.e. contribution to a more favourable relationship between return and risk of the portfolio, is derived.

While diversifying potential of cryptocurrencies is proved and already employed in the portfolio optimisation, its role as a hedge and/or safe haven is object of intensive analysis both from practitioners and academics, resulting with diversity of conclusions and opinions. Following the definition of a hedge, a diversifier and a safe haven, given by Baur and Lucey (2010) and Baur and McDermott (2010), a number of papers has been trying to make a precise distinction of these possible features of cryptocurrencies, using different samples in different periods. Mostly, the conclusion following the previous years' research is that cryptocurrencies can serve primarily as a diversifier (Bouri et al., 2017; Bouri et al., 2018; Corbet et al., 2018; Stensås et al., 2019; Bouri et al., 2020).

However, a certain heterogeneity is reported in many cases and some empirical research found safe haven and/or hedge properties of cryptocurrencies in short investment horizons, for some specific assets or markets (Bouri et al., 2017; Selmi et al., 2018; Arnerić and Mateljan, 2019; Stensås et al., 2019; Wang et al., 2019; Bouri et al., 2020; Garcia-Jorcano and Benito, 2020). Smales (2019) finds that Bitcoin is more volatile, less liquid, and costlier to transact than other assets and concludes, until the market matures, it is therefore unlikely to be worthwhile considering Bitcoin as a safe haven. With respect to all efforts up to now for examining and maybe "proving" the safe haven feature of cryptocurrencies in the times of absence of stronger and deeper crisis, the results following from those studies should be taken with caution and reinvestigated in the light of a current COVID-19 crisis.

Cryptocurrencies have also attracted a special attention as a possible substitute for gold, so called the new digital gold (Popper, 2015). Härdle et al. (2020) noticed a great similarity between Bitcoin and gold in terms of their limited supply, need for mining and psychological perspective. On the other hand, Perlaky (2019) found that gold is less volatile, has a more liquid market, trades in an established regulatory framework, has a well understood role in an investment portfolio, has little overlap with cryptocurrencies on many sources on demand and supply and, that gold is a safe haven investment.

Klein et al. (2018) tried to find relationship between gold and cryptocurrencies. They found that Bitcoin does not reflect any distinctive properties of gold other than asymmetric response in variance. Bitcoin behaves completely different from gold in particular in market distress. Bitcoin shows positive coupling effect and declines when markets are declining in shock-like situations. They repeated portfolio analysis by including CRIX instead of Bitcoin and found that CRIX seems to have marginal hedging effect for three equity indices and that the volatility dynamics of cryptocurrencies do share some similarities with gold.

Gkillas and Longin (2019) combined each equity market with Bitcoin, and found that the correlation of extreme returns sharply decreases during both market booms and crashes. Also, there is a low extreme correlation between Bitcoin and gold, indicating that both assets could provide benefits of diversification during turbulent times.

Considering the conflicting results of different research and the fact that the real crisis from the start of the cryptocurrency trading did not occur, the relationship between cryptocurrencies and gold requires further investigation.

COVID-19 pandemic is the first major crisis since the beginning of active trading with cryptocurrencies and provides a framework for testing their behaviour in the period of the extreme uncertainty and volatility of the world financial markets. The question is what features cryptocurrencies keep or maybe gain in the crisis. During and after the global financial crisis investors were seeking for a safe haven in gold, while today a great attention is put on cryptocurrencies.

Unsurprisingly, the number of papers dealing with cryptocurrencies emerged in the aftermath of the COVID crisis. Conlon and McGee (2020), using data span from March 21, 2019 through March 20, 2020, provided evidence that Bitcoin does not act as a safe haven, instead decreasing in price in lockstep with the S&P 500 as the crisis develops. Similarly, Conlon et al. (2020) found evidence that Bitcoin and Ethereum are not found to act as a safe haven for international equity markets. Tether is found to act as a safe haven in the COVID-19 crisis. Moreover, only investors in the Chinese CSI 300 index can benefit from including Bitcoin and Ethereum in their portfolios. The data span for the research is from April 2019 to April 2020. Corbet et al. (2020a) found evidence of significant growth in both returns and volumes traded, indicating that large cryptocurrencies acted as a store of value during the period from January 1, 2019 to March 31, 2020. They concluded that besides providing diversification benefits for investors, cryptocurrencies acted as a safe-haven. Similarly, Mariana et al. (2021) found that in period from July 1, 2019 until April 6, 2020, Bitcoin and Ethereum are suitable as short-term safe-havens for stocks.

Before the crisis, academic attention has been focused to Bitcoin, while other cryptocurrencies have been neglected (Canh et al., 2019). Therefore, to fill that gap, Canh et al. (2019) investigated seven cryptocurrencies and found evidence that the conditional quasi-correlation between cryptocurrencies is significantly positive and strong. Additionally, novel empirical research investigates properties of different cryptocurrencies in the COVID-19 situation. Mnif et al. (2020) detected the existence of herding behaviour in the five top cryptocurrency markets. They indicated that Bitcoin was the most efficient cryptocurrency before crisis while in the crisis period it is less efficient than Ethereum.

Our research goes one step further. The goal is to explore correlation between cryptocurrencies and asset classes other than stocks in the COVID-19 period. Considering results of movements within different cryptocurrencies (Canh et al., 2019; Mnif et al., 2020) the CRIX index is used to capture possible positive effect of other cryptocurrencies other than Bitcoin.

In the period of COVID-19 crisis, Corbet et al. (2020b), by using high frequency data, found the growth of dynamic correlations between Chinese stock exchanges with Bitcoin and gold. These results additionally motivated us to investigate dynamic correlation between gold and cryptocurrencies in detail.

Properties of Multivariate Generalized AutoRegressive Conditional Heteroskedasticity (MGARCH) models, in particular the Dynamic Conditional Correlation (DCC) model, defined by Engle (2002) and Tse and Tsui (2002), enable us to use the whole sample and in only one estimation it provides the daily conditional correlations between cryptocurrencies and other assets, both in pre-crisis and crisis period.

With this paper we are joining the ongoing wave of academic research to better understanding cryptocurrencies and their role, contributing to the existing literature in several ways. Firstly, by taking into consideration the time frame spanning from October 1, 2017 to October 1, 2020, this paper compares returns of cryptocurrencies with returns of different assets in bull and bear market conditions and reinvestigates the relationship between cryptocurrencies and gold in particular. Secondly, the use of MGARCH-DCC allows us to investigate the movement of conditional quasi-correlations between the cryptocurrencies and considered assets. Finally, CRIX is used in order to capture possible positive effects of other cryptocurrencies other than Bitcoin.

The remainder of the paper is organized as follows. Section 1 describes the data and descriptive statistics. Section 2 presents methodology. Empirical findings with discussion of the results are given in Section 3. Finally, conclusions and directions for future research are provided in Section 4.

1. Data and Descriptive Statistics

Since the cryptocurrency market was characterised by a sluggish movement of prices, market capitalization and volumes from their appearance to 2017, that period is not taken into consideration for further calculations. The surge in their prices started in 2017 and peaked in 2018, followed by the intensive trading period characterized by high volatility with continuous fluctuations until the October 2020. Therefore, only last three years of their active trading are taken into account. Based on daily closing prices from 01.10.2017 to 01.10.2020 for CRIX, Oil, Gold, REIT, Bonds, S&P500 and SSEC, the daily log-returns are calculated. Full names of the variables as well as the data sources are given in the Appendix in Table A1. Prior to their calculations, the weekend data has been excluded for CRIX.[2] Moreover, all the non-working days for S&P500 have also been excluded from further calculations in order to minimize the gaps in sample. Descriptive statistics with normality, stationarity, homoscedasticity and independence tests is given in Table 1.

Table 1 shows that the highest mean return (0.14%) is achieved for CRIX as well as the highest risk measured by standard deviation (5.02%). Moreover, it exhibits also the lowest mean return (on March 13th, 2020 of –44.66%) and the second highest mean return (22.03%). Normality of returns is tested using skewness and kurtosis test for normality (SK). The null hypothesis, that the time series

[2] Klein et al. (2018) also only consider the prices during the week for Bitcoin to synchronize their data set. Namely, they tested weekend price interpolation for the conventional assets. However, this introduced some bias to model estimation by low or virtually zero returns over the weekend.

is normally distributed, can be rejected for all variables at 1% significance level. The stationarity of returns is tested using Augmented Dickey-Fuller (ADF) test, where the null hypothesis is that a unit root is present in a time series sample. Based on 1% significance level the null hypothesis can be rejected, i.e. the variables are stationary processes. The independence of returns is tested using the Ljung-Box (LJB) test. It is a test for significant autocorrelation in a stationary time series. At lag one S&P500 and REIT returns exhibit significant autocorrelation at 1% significance.[3] Moreover, the presence of an ARCH effect is tested using a Lagrange multiplier (LM) test for the null hypothesis that the residuals do not show any autocorrelation pattern. The LM ARCH test strongly rejects the null hypothesis of no ARCH effect for all the assets except for CRIX.[4]

Table 1

Descriptive Statistics with Normality, Stationarity, Homoscedasticity and Independence Tests from 1. 10. 2017 to 5. 10. 2020

	CRIX	Oil	Gold	REIT	Bonds	S&P500	SSEC
N	756	741	728	756	746	756	688
μ	0.00138	0.00067	0.00031	–0.000108	0.00026	0.00039	0.00019
σ	0.05022	0.04323	0.00856	0.01726	0.00408	0.01452	0.01284
min	–0.44664	–0.28138	–0.05401	–0.19274	–0.02961	–0.12765	–0.04867
max	0.22027	0.42583	0.06790	0.08262	0.02710	0.08968	0.08260
α_3	–1.297	1.428	0.329	–2.391	0.186	–1.057	0.191
α_4	14.503	34.858	11.303	32.613	12.013	20.313	6.716
SK	289.03***	384.66***	137.41***	513.94***	138.22***	289.39***	69.44***
ADF	–14.218***	–17.674***	–14.713***	–13.595***	–16.588***	–14.413***	–13.315***
LJB(1)	0.0298	1.5311	3.8396*	15.2293***	0.1925	54.5339***	0.1148
LM(1)	0.813	35.968***	13.424***	58.065***	156.7***	192.259***	1.594
LM(5)	6.029	169.868***	27.377***	196.723***	239.661***	299.584***	16.885***
LM(10)	6.200	252.024***	111.225***	206.839***	239.389***	322.524***	64.646***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: The authors' calculations in STATA 13.1.

Correlation matrix for all return series for the whole period is given in Table 2. All the assets have significant correlations, somewhere positive and somewhere negative, with mostly all the other assets, except for the CRIX. Namely, in the period from October 2017 to October 2020 it exhibits small positive and insignificant correlations with Oil, Bonds and SSEC. A weak negative but significant correlation can be observed for REIT and S&P500, whereas a weak positive and significant correlation is obtained with Gold.

[3] When considering MGARCH(1,1)-DCC model with one lag of S&P500 and REIT in the mean equation, the results of the model do not improve significantly. More importantly, the conditional correlations do not change. Therefore, mean equation contains only constants for all the variables. The results are available from the authors upon reasonable request.

[4] Despite that, GARCH(1,1) is estimated for all assets. Moreover, both ARCH and GARCH coefficients for CRIX are found to be significant in MGARCH(1,1)-DCC model in Table 5.

Table 2

Correlation Matrix from 1.10.2017 to 1.10.2020

	CRIX	Oil	Gold	REIT	Bonds	S&P500	SSEC
CRIX	1						
Oil	0.0413	1					
Gold	0.1171***	–0.0232	1				
REIT	–0.0763**	0.1048***	0.1484***	1			
Bonds	0.0299	–0.1319***	0.0143	–0.2737***	1		
S&P500	–0.0702*	0.1941***	0.1438***	0.7848***	–0.5008***	1	
SSEC	0.0540	0.1481***	0.1270***	0.1417***	–0.1354***	0.2422***	1

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: The authors' calculations in STATA 13.1.

When comparing the descriptive statistics (Table 3) for the period October 2017 to December 2019, i.e. prior to crisis in the upper panel, and for the period January 2020 to October 2020, i.e. the COVID-19 crisis period in the lower panel, one may observe significantly higher risk measured by standard deviation for all assets except for CRIX. Moreover, both the lowest and the highest mean returns can be reached in the latter period. Interestingly, the mean returns are higher for all the return series, except for the S&P500 (lower mean return) and REIT (negative mean return).

Table 3

Descriptive Statistics from 1.10.2017 to 31.12.2019 (upper panel) and from 1.1.2020 to 1.10.2020 (lower panel)

	CRIX	Oil	Gold	REIT	Bonds	S&P500	SSEC
1.10.2017 to 31.12.2019							
N	566	556	546	566	556	566	515
μ	0.00064	0.00033	0.00013	0.00019	0.00013	0.00044	–0.00003
σ	0.05022	0.02007	0.00652	0.00891	0.00334	0.00897	0.01221
min	–0.30901	–0.08724	–0.02471	–0.04116	–0.01109	–0.04184	–0.04867
max	0.22027	0.14176	0.02882	0.03284	0.01236	0.04840	0.05850
α_3	–0.491	0.096	0.136	–0.602	0.011	–0.651	–0.033
α_4	7.561	8.745	4.274	5.077	3.767	7.251	5.028
1.1.2020 to 1.10.2020							
N	190	185	182	190	190	190	173
μ	0.00358	0.00166	0.00087	–0.00098	0.00064	0.00024	0.00087
σ	0.05029	0.07936	0.01288	0.03084	0.00573	0.02452	0.01457
min	–0.44664	–0.28138	–0.05401	–0.19274	–0.02961	–0.12765	–0.04597
max	0.22027	0.42583	0.06790	0.08262	0.02710	0.08968	0.08260
α_3	–3.708	0.89	0.239	–1.554	0.129	–0.767	0.539
α_4	35.848	12.235	7.994	13.532	10.919	9.606	8.685

Source: The authors' calculations in STATA 13.1.

The comparison of the correlations (Table 4) for the period October 2017 to December 2019, i.e. prior to crisis in the upper panel, and for the period January 2020 to October 2020, i.e. the COVID-19 crisis period in the lower panel, shows even more interesting results. Correlations of CRIX and all the other assets prior to crisis are weak and insignificant, whereas in the COVID-crisis period there is a significant correlation with all the variables, except for Oil. The highest negative correlation is obtained with returns on S&P500 (–0.21), while the highest positive correlation is exhibited with returns on Gold (0.29). In stable periods cryptocurrencies can be seen as a weak hedge since they are uncorrelated with all the other assets on average except for Oil. Since CRIX has a weak positive correlation with Oil, it can be seen as a diversifier. Moreover, in crisis period there is a positive and significant correlation with Gold. In the crisis period, cryptocurrencies are a strong safe heaven since they are negatively correlated to REIT and S&P500. However, a single estimate of the correlation given by Pearsons' correlation coefficient does not provide sufficient information since it is important to allow correlations to be time-varying.

T a b l e 4

Correlation Matrices from 1.10.2017 to 31.12.2019 (upper panel) and from 1.1.2020 to 1.10.2020 (lower panel)

	CRIX	Oil	Gold	REIT	Bonds	S&P500	SSEC
1.10.2017 to 31.12.2019							
CRIX	1						
Oil	0.0801*	1					
Gold	0.0136	0.0692	1				
REIT	–0.0166	0.0261	0.0164	1			
Bonds	–0.0566	–0.1488***	0.0698	0.0798*	1		
S&P500	0.0413	0.2395***	0.0646	0.4943***	–0.4149***	1	
SSEC	0.0067	0.2448***	0.0266	–0.0552	–0.1297***	0.1774***	1
1.1.2020 to 1.10.2020							
CRIX	1						
Oil	0.0286	1					
Gold	0.2886***	–0.0613	1				
REIT	–0.1544**	0.1221*	0.2147***	1			
Bonds	0.1780**	–0.1397*	–0.0369	–0.4698***	1		
S&P500	–0.2106***	0.1842**	0.1903**	0.8821***	–0.5760***	1	
SSEC	0.1712**	0.1330*	0.2594***	0.3203***	–0.1543**	0.2429***	1

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: The authors' calculations in STATA 13.1.

2. Methodology

MGARCH-DCC models by Engle (2002) and by Tse and Tsui (2002) with normal and Student *t* distributions, which allows the dynamics in correlations while the two-step procedure ensures the feasibility of the optimization and computation even if a large number of time series is considered, are applied. More precisely, they have the advantage of choosing whatever GARCH-type model for each time series, allowing for a high flexibility, while simultaneously requiring lower number of parameters compared to the vech, BEKK and factor models.[5] The result is the ease of computation as well as better model understanding. Regardless the fact that both Constant conditional correlation (CCC) and DCC models have the advantage of decomposing variance matrix into conditional volatilities and conditional correlations, CCC assumes the constant conditional correlations, which is unrealistic in most of the empirical applications (Boffelli and Urga, 2016).

The basic framework of the model applied in this paper starts from defining the mean and variance equations of GARCH (1,1) model, i.e.:

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t \\ h_t &= \alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^2 + \beta_1 \cdot h_{t-1} \end{aligned} \tag{1}$$

where in the first line of equation (1) r_t is an $m \times 1$ vector of returns at time t on m assets, μ_t is an $m \times 1$ conditional mean vector of r_t and ε_t is the vector of residuals defined as $\varepsilon_t = u_t \sqrt{h_t}$, where $u_t \mid I_{t-1} \sim N(0, H_t)$ is an *i.i.d.* process following a standard normal distribution while I_{t-1} is the information set available up to time $t-1$. In the second line of the equation (1) h_t is the conditional variance, α_0 is the constant ($\alpha_0 > 0$), α_1 the parameter that captures the short-run persistence of the ARCH effect, while β_1 represents the GARCH effect or the long-run persistence of volatility ($0 \le \alpha_1 + \beta_1 < 1$). Therefore, m univariate GARCH (1,1) models are fitted in the first step of the estimation procedure.

In the second step the DCC model by Engle (2002) starts from the decomposition of the matrix H_t, i.e. the variance-covariance matrix of returns:

$$H_t = D_t R_t D_t \tag{2}$$

where D_t is the diagonal matrix of conditional standard deviations computed by univariate GARCH (1,1) models from the first step and R_t is the conditional correlation matrix of returns which is time dependent and takes the following form

$$R_t = \mathrm{diag}\left(q_{11,t}^{-1/2}, q_{22,t}^{-1/2}, ..., q_{mm,t}^{-1/2}\right) Q_t \mathrm{diag}\left(q_{11,t}^{-1/2}, q_{22,t}^{-1/2}, ..., q_{mm,t}^{-1/2}\right) \tag{3}$$

The $m \times m$ symmetric positive definite matrix Q_t is given by:

$$Q_t = \left(1 - \lambda_1 - \lambda_2\right)\bar{Q} + \lambda_1 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right)' + \lambda_2 Q_{t-1} \tag{4}$$

[5] Moreover, vech models require additional constraints to ensure the positive semidefinitiveness of the variance-covariance matrix.

where λ_1 and λ_2 are time invariant parameters while the constraint $\lambda_1 + \lambda_2 < 1$ ensures that the process is stationary and where $\bar{Q}$ is the sample counterpart of the unconditional correlation matrix. In this two-step optimization procedure, the parameters are estimated using maximum likelihood.

Although normal distribution has good mathematical properties, due to inherent leptokurtosis of financial time series, one of the proposed distributions to deal with those properties is the Student *t* distribution. The conditional distribution of innovation $u_t \mid I_{t-1} \sim N(0, H_t)$ is replaced by $u_t \mid I_{t-1} \sim f_t(u_t, \nu)$ and $f_t(u_t, \nu) = \frac{\Gamma\left[(n+\nu)/2\right]}{(\pi\nu)^{n/2}\,\Gamma(\nu/2)} \left|H_t\right|^{-1/2} \times \left[1 + \nu^{-1} u_t^{'} H_t^{-1} u_t\right]^{-(n+\nu)/2}$ where ν are the degrees of freedom (Hsu Ku, 2008).

3. Results and Discussion

Engels' (2002) and Tse and Tsuis' (2002) models with normal and Student *t* distributions in MGARCH(1,1)-DCC model specification with only constants in the mean equation, is estimated for CRIX, Oil, Gold, REIT, Bonds, S&P500 and SSEC for the period from October 1, 2017 to October 1, 2020. Engels' model with student *t* distribution is chosen as the most appropriate[6] and its results are presented in the Table 5 along with parameter estimates and standard model diagnostics.

All parameters of all the univariate GARCH(1,1) models are statistically significant at 1% significance level, as well as the estimates of λ_1 and λ_2 which indicate that conditional correlations are highly persistent. Positive parameters α_0, α_1 and β_1 ensure that estimated variances of returns are positive, while the satisfied constraints $\alpha_1 + \beta_1 < 1$ and $\lambda_1 + \lambda_2 < 1$ ensures that the process is stationary. The degrees of freedom are equal to 6.08, which suggests that the fitted multivariate Student *t* distribution if far from the multivariate normal and it is characterized by moderately fat tails.

Moreover, a diagnostic checking of the standardized residuals of each GARCH(1,1) model separately yields to a conclusion that there is no ARCH effect. All this indicates that MGARCH(1,1)-DCC model with Student *t* distribution, estimated using maximum likelihood estimation method in two steps is correctly specified.

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[6] Log-likelihood, AIC and BIC information criteria as well as Likelihood-ratio test confirmed the selection. The results are robust to selection of any DCC method.

T a b l e 5

Estimated Parameters with Standard Model Diagnostics for M-GARCH(1,1)-DCC Model with Student *t* Distribution for the Period 1.10.2017 to 1.10.2020

	CRIX	**Oil**	**Gold**	**REIT**	**Bonds**	**S&P500**	**SSEC**
μ	0.00174	0.00135*	0.000195	0.00100***	0.000166	0.00152***	0.000697*
	(0.00163)	(0.00074)	(0.000255)	(0.000372)	(0.000119)	(0.000278)	(0.000416)
α_1	0.0670***	0.215***	0.146***	0.176***	0.185***	0.185***	0.100***
	(0.0258)	(0.0418)	(0.0432)	(0.0342)	(0.0477)	(0.0354)	(0.0329)
β_1	0.919***	0.709***	0.840***	0.736***	0.691***	0.715***	0.885***
	(0.0393)	(0.0496)	(0.0571)	(0.0440)	(0.0813)	(0.0465)	(0.0393)
α_0	0.0000484	0.000046**	0.0000025	0.000013***	0.0000021**	0.0000085***	0.0000048
	(0.00006)	(0.00002)	(0.000002)	(0.000004)	(0.0000008)	(0.000003)	(0.000003)
$\alpha_1+\beta_1$	0.986	0.924	0.986	0.912	0.876	0.900	0.985
LM(1)	0.151	2.407	1.127	0.534	0.353	0.674	0.820
LM(5)	3.022	5.556	2.059	13.849**	2.432	6.590	0.669
$\lambda_1+\lambda_2$	0.9275						
λ_1	0.0135***						
	(0.00496)						
λ_2	0.914***					*LL*	13847.9
	(0.0302)					*AIC*	–27591.79
v	6.081***					*BIC*	–27359.47
	(0.608)					*N*	644

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: The authors' calculations in STATA 13.1.

The matrix of long-run or conditional correlations is given in the Table 6. CRIX exhibits weak and insignificant conditional correlations with all the observed variables except for the weak positive and significant conditional correlation obtained with Gold and Oil. In the whole period cryptocurrencies can be seen as a weak hedge for all assets except for Gold and Oil, since they are uncorrelated with all the other assets on average. Cryptocurrencies can be seen as a diversifier for Gold and Oil, exhibiting a weak positive correlation on average.

T a b l e 6

Conditional Correlations for MGARCH(1,1)-DCC Model for the Period 1.10.2017 to 1.10.2020

	CRIX	**Oil**	**Gold**	**REIT**	**Bonds**	**S&P500**
Oil	0.0951*					
	(0.0534)					
Gold	0.0963*	0.0571				
	(0.0515)	(0.0534)				
REIT	–0.0145	0.0699	0.0402			
	(0.0536)	(0.0545)	(0.0523)			
Bonds	–0.0495	–0.195***	0.0606	0.0256		
	(0.0529)	(0.0516)	(0.0518)	(0.0541)		
S&P500	0.0483	0.286***	0.0528	0.549***	–0.386***	
	(0.0531)	(0.0504)	(0.0527)	(0.0376)	(0.0451)	
SSEC	0.0684	0.249***	0.109**	0.0171	–0.126***	0.211***
	(0.0512)	(0.0482)	(0.0501)	(0.0509)	(0.0489)	(0.0484)

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: The authors' calculations in STATA 13.1.

However, Table 6 presents only long-run conditional correlation. The estimated daily conditional correlations of DCC model enables us to move forward and explain their movements in pre-crisis and crisis period. The descriptive statistics for dynamic conditional correlation between CRIX and all other assets is given in Table 7 and their movement is given in Figure 1.

Table 7

Descriptive Statistics for Dynamic Conditional Correlation between CRIX and All other Assets from 1.10.2017 to 31.12.2019 (upper panel) and from 1.1.2020 to 1.10.2020 (lower panel)

	Oil	**Gold**	**REIT**	**Bonds**	**S&P500**	**SSEC**
1.10.2017 to 31.12.2019						
μ	0.03448	0.07557	–0.06519	0.01195	–0.04217	0.02033
σ	0.02426	0.02282	0.02358	0.02946	0.03463	0.03153
min	–0.03904	–0.01428	–0.12485	–0.10299	–0.20050	–0.08539
max	0.09591	0.14461	0.01084	0.08232	0.07949	0.10048
1.1.2020 to 1.10.2020						
μ	0.02907	0.11935	–0.05807	0.03848	–0.05424	0.03346
σ	0.03731	0.03355	0.03201	0.03233	0.03241	0.02613
min	–0.03588	0.01983	–0.10930	–0.03101	–0.10832	–0.03097
max	0.15515	0.25504	0.08567	0.12740	0.06643	0.07555

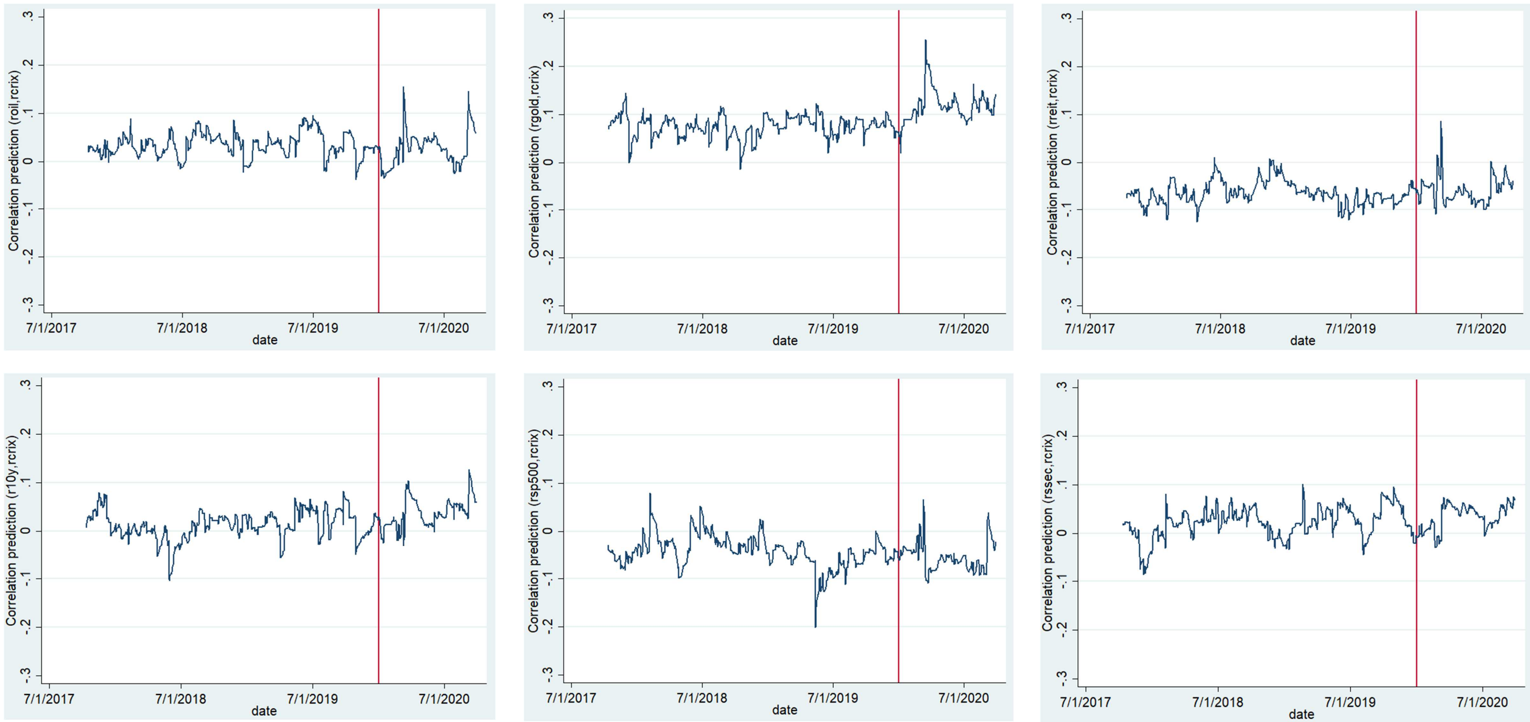
Source: The authors' calculations in STATA 13.1.

There is a weak and positive conditional correlation in the whole period between CRIX and Oil. Moreover, their values slightly decrease on average in the crisis period, except for the two peaks in the crisis. Constant conditional correlations through the whole period caused the significance in the estimate of the long-run conditional correlation in the DCC model. Small and insignificant relationship between Bitcoin and Brent crude oil is found in Derbali et al. (2020). Additionally, recent research of Kumah and Odei-Mensah (2022) confirmed that crude oil can not be used as hedge.

The results for Gold show also weak and positive conditional correlation in stable period (0.075 on average), while in the crisis period a significant rise in the conditional correlations (0.119 on average) can be observed with the upward trend (Figure 1 and Table 7). This is in line with the statistically significant estimate of the long-run conditional correlation between Gold and CRIX (Table 6). Similar results are obtained in Corbet et al. (2020b) using high-frequency data for the pre-crisis and crisis period, but they cover only short crisis sample period, while the Gkillas and Longin (2019) did not find correlation between Gold and Bitcoin. Therefore, this relationship has to be further investigated with longer crisis period.

F i g u r e 1

Dynamical Conditional Correlations between the Returns of All the Variables Used in Model with CRIX (CRIX) in Period from 1.10.2017 to 1.10.2020, where the Vertical Line Indicates 1.1.2020



Source: The authors' calculations in STATA 13.1.

The results for REIT and S&P500 show negative conditional correlations on average in the whole period. Moreover, negative conditional correlations of CRIX with REIT and S&P500 can be observed in more than 90% of days (Figure 1). Similar results for S&P500 and two cryptocurrencies (Bitcoin and Ethereum) are obtained in Mariana et al. (2021).

Although not statistically significant, there is positive conditional correlations of CRIX with Bonds and SSEC. Corbet et al. (2020b) also showed positive correlations with Chinese exchanges and Bitcoin.

Moreover, in only several days in March 2020, CRIX exhibits positive correlation with all the assets, since its value decreased along with the values of other assets at the start of the COVID-19 crisis. This is in line with the findings of Conlon and McGee (2020) for S&P500 and Bitcoin.

Since the dynamics of the conditional correlations between all pairs of assets in the model are governed only by λ_1 and λ_2, it can lead the MGARCH-DCC with more than two assets in the model to lose the ability to determine the precise dynamics of conditional correlations between particular pair of assets.

Therefore, to confirm that the bias introduced by the MGARCH-DCC model (estimation of single λ_1 and λ_2 for all pairs of assets) does not meaningfully impact the results, i.e. to verify the robustness of the results, six separate bivariate MGARCH-DCC models between CRIX and each of six traditional assets are estimated. The conditional correlations for six bivariate MGARCH-DCC models are given in Table 8. The robustness check confirms the results from the Table 6.

Table 8

Conditional Correlations for Six Bivariate MGARCH(1,1)-DCC Models for the Period 1.10.2017 to 1.10.2020

	CRIX
Oil	0.0826* (0.0456)
Gold	0.0896 (0.0623)
REIT	–0.0203 (0.0383)
Bonds	–0.0290 (0.0786)
S&P500	0.0013 (0.0444)
SSEC	0.0057 (0.0444)

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: The authors' calculations in STATA 13.1.

The descriptive statistics for dynamic conditional correlation between CRIX and all other assets obtained from the estimated six bivariate MGARCH-DCC models is given in Table 9.

The descriptive statistics in both size and sign confirm the results obtained from Table 7. In the crisis period higher absolute values of conditional correlations can be observed for all the assets except for oil. Namely, crisis period yielded higher positive conditional correlations for Gold and SSEC, and higher negative conditional correlations with REIT, Bonds and S&P500. Only conditional correlations of CRIX and Oil fell in the crisis period.

T a b l e 9

Descriptive Statistics for Dynamic Conditional Correlation between CRIX and All other Assets from 1.10.2017 to 31.12.2019 (upper panel) and from 1.1.2020 to 1.10.2020 (lower panel) from Six Bivariate MGARCH-DCC Models

	Oil	**Gold**	**REIT**	**Bonds**	**S&P500**	**SSEC**
1.10.2017 to 31.12.2019						
μ	0.0332	0.0554	–0.0590	–0.0081	–0.0363	0.0255
σ	0.0258	0.0333	0.0154	0.0328	0.0275	0.0586
min	–0.0216	–0.0322	–0.0807	–0.0754	–0.0946	–0.1379
max	0.0963	0.1374	–0.0362	0.0700	0.0281	0.1486
1.1.2020 to 1.10.2020						
μ	0.0128	0.0905	–0.0615	–0.0395	–0.0675	0.0679
σ	0.0210	0.0239	0.0150	0.0327	0.0167	0.0644
min	–0.0308	0.0235	–0.0807	–0.0241	–0.1014	–0.0964
max	0.0677	0.1424	–0.0363	0.0980	–0.0308	0.1979

Source: The authors' calculations in STATA 13.1.

Conclusion

The aim of this paper was to reinvestigate the properties of cryptocurrencies in the COVI9-19 crisis. For that purpose, they are compared to the traditional assets, i.e. S&P500 and SSEC indices, crude oil and gold fixing prices, US Real Estate Investment Trust Index and U.S. Treasury Bond Current 10-Year Index. Conditional correlations indicate that for the crude oil prices, as well as U.S. Treasury Bond Current 10-Year Index and SSEC, cryptocurrencies can be seen as a diversifier. Cryptocurrencies are a weak hedge for the US Real Estate Investment Trust Index and S&P500. The results of the daily dynamic conditional correlations confirmed that relationship between cryptocurrencies and most assets did not significantly change in crisis. Only a rise in positive correlation with gold fixing prices can be observed in the COVID-crisis period. Further investigation should be conducted to test whether cryptocurrencies will lose their diversifier properties with gold or not.

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Appendix

Table A1

Variables in the Model, with Their Full Names and Sources

Variables	Full name	Source
CRIX	Log returns on CRIX, closing data.	<http://data.thecrix.de/#services> [06.10.2020].
Oil	Log returns on Crude Oil Prices: Brent – Europe, Dollars per Barrel, Daily, Not Seasonally Adjusted.	[DCOILBRENTEU], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/DCOILBRENTEU>, November 4, 2020.
Gold	Log returns on Gold Fixing Price 10:30 A.M. (London time) in London Bullion Market, based in U.S. Dollars, U.S. Dollars per Troy Ounce, Daily, Not Seasonally Adjusted.	[GOLDAMGBD228NLBM], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/GOLDAMGBD228NLBM>, November 4, 2020.
REIT	Log returns on Wilshire US Real Estate Investment Trust Total Market Index (Wilshire US REIT), Index, Daily, Not Seasonally Adjusted.	[WILLREITIND], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/WILLREITIND>, November 4, 2020.
Bonds	Log returns on S&P U.S. Treasury Bond Current 10-Year Index.	<https://www.spglobal.com/spdji/en/indices/fixed-income/sp-us-treasury-bond-current-10-year-index/#overview> [1.11.2020].
S&P500	Log returns on S&P 500 Index, close.	Thomson Reuters Eikon [06.10.2020].
SSEC	Log returns on Shanghai SE Composite Index, close.	Thomson Reuters Eikon [06.10.2020].