IRANIAN ECONOMIC REVIEW
Print ISSN: 1026-6542
Online ISSN: 2588-6096
https://ier.ut.ac.ir/
University of Tehran

Cryptocurrencies' Time to Shine in the World

Sana Braïek[a,*], **Ahmed Jeribi**[b]

a. Department of Economics and Quantitative Methods, University of Sousse, Laboratory Research for Economy, Management and Quantitative Finance, Sousse, Tunisia
b. Department of Finance, Faculty of Economics and Management of Mahdia, Hiboun, Tunisia
* Corresponding Author, E-mail: sana.braiek@isffs.u-sousse.tn

Article Info

Article Type: Research Article

Article History:
Received: 07 June 2021
Received in revised form: 18 November 2021
Accepted: 26 December 2021
Published online: 03 December 2023

Keywords:
Developed and BRICS Stock Markets, COVID-19 Pandemic, Gold, Digital Assets, VIX, WTI, C-Vine Copula.

JEL Classification:
C22, C5, G1.

ABSTRACT

Using the time-varying copula, we investigate the dynamic dependence between developed and BRICS stock market indices, digital assets, oil, and gold prices for January 2, 2016 to March 31, 2020. Our findings reveal that cryptocurrencies are considered hedge and diversifier assets before the 2020 global pandemic. Dash, Bitcoin, Monero, and Ripple may serve as good protectors against extreme stock markets' co-movements during the COVID-19 outbreak in many countries. Risks among oil markets cannot be hedged by the kind of cryptocurrencies. In addition, the dynamic dependence between cryptocurrencies and Gold follows the same trend except for a couple of Gold-Dash. These results have important implications for investors and market participants to track the progress of the different safe-haven instruments. Thus, portfolio managers may take into account the few eligible cryptocurrencies for inclusion in their portfolios. Speculators in stock and cryptocurrency markets may use a spread technique to boost their portfolio return.

Cite this article: Braïek, S., & Jeribi, A. (2023). Cryptocurrencies' Time to Shine in the World. *Iranian Economic Review, 27*(4), 1154-1198. DOI: 10.22059/IER.2022.85770

DOI: 10.22059/IER.2022.85770
Publisher: University of Tehran Press.

1. Introduction

The world's geo-economics and political climate had rarely been so fraught. The last decade has witnessed the occurrence of several crises such as the 2010-2011 European debt crisis and the Greek debt crisis. The US-China trade war, the tensions between France and Germany, problems in key emerging countries such as Turkey and Argentina, the 2018 Bitcoin crash, and the increasingly bitter political conflict in the US are the most significant events surrounding the last decade. The coronavirus pandemic and the oil price war between Russia and Saudi Arabia are crucial events marking the beginning of the third decade of this cycle.

March 24, 2020, Goldman Sachs' report[1] indicated that the COVID-19 has pushed the global economy into a recession of historic proportions. It halted the longest-lasting equity bull market on record. In addition, the ongoing oil price war between Moscow and Riyadh triggered a major fall in the price of oil and leads to stock market panic.

Due to the growth of cross-market linkages and the increase in financial markets' volatility, the diversification of portfolios through hedges is becoming more relevant. In particular, during the global financial crisis, gold prices rose dramatically, while other assets suffered losses (Beckmann et al., 2015). Gold's hedging and safe haven properties were investigated in some depth with Baur and Lucey (2010) whose findings show that gold is a hedge and safe haven for stocks but not for bonds, while gold is also found to function as a safe haven just for 15 days after a market collapse. This research is extended by Baur and McDermott (2010) who demonstrate the role of gold as a safe haven for equities but not for all examined countries. By using the Baur and McDermott (2010) framework, Pasutasarayut and Chintrakarn (2012) find that gold is neither a safe haven nor a hedge on the Thai economy. Bredin et al. (2015) use wavelet analysis to show that gold can be used as a safe haven for up to one year while Lucey and Li (2014) found that the gold's safe-haven property is unstable, suggesting that the capacity of gold to serve as a hedge and a safe haven fluctuates over time.

Dyhberg (2016) indicated that the global uncertainty crisis has eased the emergence of Bitcoin which is proposed by Nakamoto (2008) in a paper entitled "Bitcoin: A Peer-to-Peer Electronic Cash System", as an alternative payment system independent of any central authorities or central banks. Bitcoin has also been widely compared to commodities, especially gold, as its inventor intended. Besides the conceptual similarity of "mining," Bitcoin and Gold have many characteristics in common. Even if they do not claim the future cash flows, their value is related to their demand and supply. The relationship between Bitcoin and other financial assets and determining whether Bitcoin can be listed as a diversifier, hedge, or safe haven against other financial assets is a research area that has gained some attention in the literature. Dyhrberg (2016) reveals that Bitcoin can be a hedge against the US dollar and the UK stock market, sharing similar hedging abilities to gold. Bouri et al. (2017a) illustrated that Bitcoin can only be a hedge against global uncertainty in short investment horizons and in bulls. In the same line of results, Bouri et al. (2017b) show limited evidence of Bitcoin's hedging and safe properties, but it may still be an effective diversifier. In addition, Corbet et al. (2018) suggested that Bitcoin can play a role in the portfolio of an investor, Shahzad et al. (2019) demonstrated that Bitcoin can be a safe haven, although its role varies in time and differs across markets. Kajtazi and Moro (2019), Plantakis and Urquhart (2020) as well as Fakhfekh and Jeribi (2020), Ghorbel and Jeribi (2021b), and Lahiani et al. (2021) found evidence that Bitcoin has some capabilities to hedge and advantages to diversification.

Driven by the popularity of Bitcoin, a large variety of other cryptocurrencies, known as altcoins, have risen. The results of Corbet et al. (2018) are similar to

[1]. Equity Research, Global Macro Research ISSUE 87 | March 24, 2020

those of Corbet et al. (2019) suggesting that cryptocurrencies are rather isolated from the other markets. Aslanidis et al. (2019) explored the conditional associations between four cryptocurrencies (Bitcoin, Monero, Dash, and Ripple), S&P500, bond, and gold. Their results claimed that cryptocurrencies are strongly correlated. In addition, the correlations between cryptocurrencies and traditional financial assets are negligible. Tiwari et al. (2019), Charfeddine et al. (2020), Jeribi et al. (2020), Jeribi and Ghorbel (2021), and Jeribi and Fakhfekh (2021) argued that cryptocurrencies may be ideal for financial diversification supporting the idea that the relationship between cryptocurrencies and other conventional assets is negligible and sensitive to financial and economic shocks.

Recently, gold and cryptocurrencies' hedging and safe haven capabilities are tested in the 2020 global crisis with the emergence of the COVID-19 pandemic. Using three variants of multivariate GARCH models, Fakhfekh et al. (2021)'s study proved that both Bitcoin and Gold have notable hedging commodity characteristics, whereas the other assets appear to act as diversifiers. Conlon and McGee (2020) found that Bitcoin and Ethereum are not safe havens for the majority of international equity markets. In the same line of results, Garcia-Jorcano and Benito (2020) found that Bitcoin can be considered as a hedge asset under normal market conditions. However, it changes to be a diversifier asset under extreme market conditions. This result is in line with Jeribi and Snene_Manzli (2021) who investigated the safe haven property of Gold and cryptocurrencies for the Tunisian stock market during the COVID-19 pandemic and find out that the yellow metal and cryptocurrencies acted mostly as diversifiers during the pandemic. Shahzad et al. (2020) suggested that the diversification benefits offered by gold are comparatively more stable and much higher than those of Bitcoin. Also, Gorbel and Jeribi (2021a) and Jeribi and Masmoudi (2021) indicated that Bitcoin and gold are considered hedges for the US investors before the 2020 global crisis. However, unlike gold, digital assets are not a safe haven for US investors during the 2020 global financial crisis. More recently, when investigating the safe haven property of five major cryptocurrencies and Gold for the BRICS stock market, Jeribi et al. (2021) found that during the financial crisis, all five cryptocurrencies were proven to be a safe haven for three emerging markets, namely Brazil, China, and Russia. However, Gold is proven to be a safe haven only for Russia and Brazil.

Another commodity that relates to cryptocurrencies is energy. Indeed, the cryptocurrencies that rely on mining are major energy consumers, as energy is an important input for these cryptocurrencies. The relation between cryptocurrencies and energy has been identified for Bitcoin (see Bouri et al., 2017b), indicating that the value of Bitcoin reflects the cost of production, which is dominated by energy consumption, and that the lower value of Bitcoin's fundamental value is calculated by the cost of energy involved in its mining (Garcia and Schweitzer, 2015). Nonetheless, Ciaian et al. (2016) provide evidence that oil prices have a significant effect on oil prices only in the short term, although Baur et al. (2018) found that Bitcoin returns are not associated with oil or gold commodities both in normal times and in periods of financial instability. In the meantime, Bouri et al. (2017a) have shown that Bitcoin is negatively correlated with the commodity index, but the relation disappears when considering weekly data. The time-varying relationship between commodities and Bitcoin is verified for energy by Bouri et al. (2017b) who concluded that Bitcoin and the global energy commodity would only be positively but weakly correlated after 2013 within their 2010-2015 study. (See also Selmi et al., 2018). Recently, Sharif et al. (2020), Salisu et al. (2020), and Gorbel and Jeribi (2021b) show that the COVID-19 pandemic is responsible for risk transmission across commodities especially oil and financial markets. Contrary to gold, Gorbel and Jeribi (2021b) found that Bitcoin cannot be considered as a safe haven during the global pandemic when investing in crude oil. Also, using the Markov-Switching-BEKK-GARCH model, Ghorbel and Jeribi (2021c) demonstrated a volatility spillover from energy assets to financial assets. Their results show a significant level of dynamic correlation between energy assets and stock indexes in the high regime, demonstrating the COVID-19's contagion effect. However, during the COVID-19 crisis, the dynamic conditional link between energy assets and gold prices declined.

In this context, we used the pair copula construction with time varying -copula method to study the dynamic dependence between the developed and BRICS stock market indices, five cryptocurrencies, oil, and gold prices highlighting the hedging and safe haven properties of cryptocurrencies during the COVID-19 outbreak and the Russia–Saudi Arabia oil price war.

This study adds to the existing literature in four ways. Firstly, the latter researches that studied the volatility dynamics and correlations between cryptocurrencies and other assets have used multivariate GARCH models like BEKK (Klein et al., 2018), DCC (Bouri et al., 2017a; Aslanidis et al., 2019; Ghorbel and Jeribi, 2021a), ADCC (Gajardo et al., 2018), copula-ADCC-EGARCH model, (Tiwari et al., 2019) and the Student-t copula (Charfeddine et al., 2020). In this study, we used the C-vine copula method based on the time varying pair copula. Secondly, unlike the few papers focusing on the hedging potential of Bitcoin (Dyhrberg, 2016; Guesmi et al., 2019; Charfeddine et al., 2020) and Ethereum (Charfeddine et al., 2020), this work extends the studied cryptocurrencies and includes Dash, Monero, and Ripple in the analysis. Thirdly, despite the considerable attention accorded to BRICS markets from academics to investigate their significant economic and financial development in the last decade, the relevant body of the empirical research remains surprisingly limited, to the best of our knowledge, in understanding the dynamic associations between the BRICS markets which are considered as diversifier assets (Bowman and Comer, 2000; Lehkonen and Heimonen, 2014; Syriopoulos et al., 2015; Mensi et al., 2017; 2018) and digital assets. This research paper attempts to fill some of the gaps in the topic and contributes a range of fruitful and innovative empirical findings. Finally, the coronavirus pandemic outbreak and Russia–Saudi Arabia oil prices are considered when understanding the linkages between the traditional financial assets and cryptocurrencies.

The content of this paper is structured as follows. The next section discussed the methodology. The data and preliminary statistics are presented in Section 3. Section 4 discussed the empirical results and finally, Section 5 concludes the paper.

2. Methodology

2.1 Properties of Conditional Variance

GARCH (1, 1)

Throughout previous studies, many authors successfully modeled financial time series by ARMA-GARCH models.

Mean equation:

$$R_{i,t} = \mu_i + \phi_i R_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

$$\varepsilon_{i,t} = Z_{i,t}\sqrt{h_{i,t}} \quad , Z_{i,t} \sim T \tag{2}$$

Variance equation:

$$h_{i,t}^2 = \omega + \alpha_i \varepsilon_{i,t-i}^2 + \beta_j h_{i,t-j}^2 \tag{3}$$

where i=1,…,10.

The Hyperbolic GARCH Model (HYGARCH)

Developed by Davidson (2004), the hyperbolic GARCH (HYGARCH) model is constructed in a way that allows the model not only to reproduce long memory features in the volatility of many financial time series but also (unlike FIGARCH) to be covariance stationery. The HYGARCH(1,d,1) process models the conditional variance as:

$$\sigma_t^2 = \boldsymbol{\omega} + \{\mathbf{1} - \boldsymbol{\beta}(\boldsymbol{L}) - \boldsymbol{\phi}(\boldsymbol{L})[(\mathbf{1} - \boldsymbol{\tau}) + \tau(1-L)^d]\}x_t^2 + \beta\sigma_{t-1}^2 \tag{4}$$
$$=\omega(1-\beta)^{-1} + \lambda(L)x_t^2$$

Where $\lambda(L) = \{1 - (1 - \boldsymbol{\beta}(\boldsymbol{L}))\boldsymbol{\phi}(\boldsymbol{L})[(\mathbf{1} - \boldsymbol{\tau}) + \tau(1-L)^d]\}, \boldsymbol{\omega} > 0, \phi < 1, \beta < 1, 0 \leq d < 1$

and $\lambda \geq 0, \lambda(L) = \lambda_1 L + \lambda_2 L^2 + \cdots,\quad \lambda_j \geq 0\ for\ j = 1,2 \ldots L$ is the lag operator and the HGARCH model reduces to FIGARCH and IGARCH when τ=1, τ=0 respectively.

EGARCH Model

Nelson (1991) proposed the following exponential GARCH (EGARCH) model to allow for leverage effects:

$$h_t = a_0 + \sum_{i=1}^{p} a_i \frac{|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} b_j h_{t-j} \tag{5}$$

where $h_t = log\sigma_t^2$ or $\sigma_t^2 = e^{ht}$. Note that when ε_{t-i} is positive or there is "good news", the total effect of ε_{t-i} is $(1+\gamma_i)|\varepsilon_{t-i}|$; in contrast, when ε_{t-i} is negative or there is "bad news", the total effect of ε_{t-i} is $(1-\gamma_i)|\varepsilon_{t-i}|$. Bad news can have a larger impact on volatility, and the value of γ_i would be expected to be negative.

FIGARCH Model

The basic GARCH (1, 1) model can be written as an ARMA (1, 1) model in terms of squared residuals. In the same spirit, for the GARCH (p, q) model:

$$\sigma_t^2 = a + \sum_{i=1}^{P} a_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2 \tag{6}$$

that can be rewritten as:

$$\phi(L)\varepsilon_t^2 = a + b(L)u_t \tag{7}$$

where $u_t = \varepsilon_t^2 - \sigma_t^2$.

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_m L^m$$
$$b(L) = 1 - b_1 L - b_2 L^2 - \cdots - b_q L^q$$

with $m = max(p, q)$ and $\phi_i = a_i + b_i$. Obviously equation (4) represents an $ARMA\,(m, q)$ process in terms of squared residuals ε_t^2 with u_t being a MDS disturbance term.

The high persistence in GARCH models suggests that the polynomial $\phi(z) = 0$ may have a unit root, in which case the GARCH model becomes the integrated GARCH (IGARCH) model. See Nelson (1990) for which the unconditional variance does not exist. To allow for high persistence and long memory in the conditional variance while avoiding the complications of IGARCH models, extend the $ARMA(m, q)$ process in (4) to a $FARIMA(m, d, q)$ process as follows:

$$\phi(L)(1 - L)^d \varepsilon_t^2 = a + b(L)u_t \tag{8}$$

where all the roots of $\phi(z) = 0$ and $b(z) = 0$ lie outside the unit circle. When d=0, this reduces to the usual GARCH model; when d = 1, this becomes the IGARCH model; when 0 < d < 1, the fractionally differenced squared residuals, $(1 - L)^d \varepsilon_t^2$, follow a stationary ARMA(m, q) process. The above FARIMA process for ε_t^2 can be rewritten in terms of the conditional variance σ_t^2:

$$b(L)\sigma_t^2 = a + [b(L) - \phi(L)(1 - L)^d]\varepsilon_t^2 \tag{9}$$

Baillie et al. (1996) referred to the above model as the fractionally integrated GARCH or FIGARCH (m, d, q) model. When 0 < d < 1, the coefficients in $\phi(L)$ and $b(L)$ capture the short-run dynamics of volatility, while the fractional difference parameter d models the long-run characteristics of volatility.

2.2 Multivariate Dependence with Canonical Vine Copula

A vine is a graphical representation based on Pair Copula Construction (PCC), introduced by Bedford and Cooke (2001; 2002). The idea is to construct multivariate distributions using bivariate and conditional bivariate copulas as building blocks. They called the structure a Regular vine (R- vine) since it is based on graphical trees. Aas et al. (2009) focused on the canonical vine (C-vine) and drawable vine (D-vine) copulas which are two special cases of the R- vine. In our paper, we consider the C-vine copulas with different hierarchical tree structures.

Definition (Vine) $V = (T_1, \ldots, T_{d-1})$ is a vine on *d* elements if:

- T_1 is a tree with nodes $N_1 = \{1, \ldots, d\}$ and a set of edges E_1.
- For *i=2,…,d-1*, T_i is a tree with nodes $N_i = E_{i-1}$ and a set of edges E_i

V is called a **regular vine** on *d* elements if we add a third condition to the two previous ones:

- For *i=2,…,d-1*, if $a = \{a_1, a_2\}$ and $b = \{b_1, b_2\}$ are nodes of T_i linked by an edge, then exactly one of the a_i equals one of the b_i .

Depending on the types of trees, different vine copulas can be constructed and two special cases of R-vine may exist, C-vine and D-vine copulas.

C-Vine Copula

A C-vine copula is an R-vine copula for which each tree has a unique node that connects with all the other nodes. Thus, the joint probability density function of *d*-dimension for C-vine is given by:

$$f(x_1, x_2, \dots, x_d) = \prod_{k=1}^{d} f_k(x_k) \prod_{h=2}^{d} \prod_{h=1}^{d-1} c_{1,h}\,(F_1(x_1), F_h(x_h)) \tag{10}$$

$$\prod_{j=2}^{d-1} \prod_{i=1}^{d-j} c_{j,j+1|1,\dots,j-1}\,(F\big(\,x_j \mid x_1, \dots, x_{j-1}\,\big), F(x_{j+1} \mid x_1, \dots, x_{j-1})$$

where $c_{j,j+1|1,\dots,j-1}$ is the conditional copula density (the index *i* identifies the trees and index *j* identifies the edges in each tree), f_k denote the marginal densities (*k=1,…,d*) and the conditional distribution function of the $x_i$variable conditional on the variable x_i, is given by Joe (1997):

$$F_{i|j}(x_i, x_j) = \frac{\partial c_{i,j}(F_i(x_i), F_j(x_j))}{\partial F_j(x_j)} \tag{11}$$

Indeed, a*d*-dimensional C-vine copula with *d* nodes and *d (d-1)/2* pair-copulas are arranged on *d-1* trees.

We illustrate an example of *4*-dimensional C-vine density decomposition and its hierarchical tree structure:

$$\begin{aligned} f(x_1, x_2, x_3, x_4) = {} & c_{1,2}\big(F_1(x_1), F_2(x_2)\big).\, c_{1,3}\big(F_1(x_1), F_3(x_3)\big)\,.\, c_{1,4}\big(F_1(x_1), F_4(x_4)\big) \\ & .\, c_{2,3|1}\Big(F_{2|1}(x_2 \mid x_1), F_{3|1}(x_3 \mid x_1)\Big)\,.\, c_{2,4|1}\Big(F_{2|1}(x_2 \mid x_1), F_{4|1}(x_4 \mid x_1)\Big) \\ & .\, c_{3,4|1,2}\Big(F_{3|1,2}(x_3 \mid x_1, x_2), F_{4|1,2}(x_4 \mid x_1, x_2)\Big) \\ & .\, f_1(x_1).\, f_2(x_2).\, f_3(x_3).\, f_4(x_4) \end{aligned} \tag{12}$$

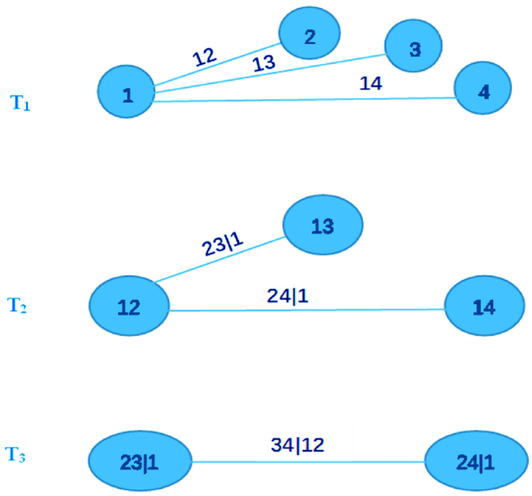


Figure 1. Four Dimensional C-vine Structure with three Trees
Source: Research finding.

Time-Varying and Static Bivariate Copula Models

We present the bivariate copula that we use as components of the C-vine. For each of these copulas, we estimate both a static and a dynamic version, and, again, for each pair of returns, we use the AIC to choose the best of all static and dynamic copula.

Gaussian Copula

The *d*-dimensional Gaussian copula (normal copula) function is of the form:

$$\boldsymbol{C}(u_1, u_2, \dots, u_d) = \Phi_R(\Phi^{-1}(u_1), \Phi^{-1}(u_2), \dots, \Phi^{-1}(u_d)) \tag{25}$$

$$= \int_{-\infty}^{\Phi^{-1}(u_1)} \dots \int_{-\infty}^{\Phi^{-1}(u_d)} \frac{1}{(2\pi)^{\frac{d}{2}}|R|^{\frac{1}{2}}} exp\left(\frac{-1}{2} y'R^{-1}y\right) dy_1 \dots . dy_d$$

where Φ is the cumulative distribution function of the standard normal distribution, Φ_{Σ} is the multivariate normal cumulative distribution function with mean zero and $m \times m$ correlation matrix R , Φ^{-1} is the inverse function of the standard univariate normal distribution, $|R|$ is the determinant of the correlation matrix R and $y = (y_1, \dots, y_d)$.

The density function of the Gaussian copula is given by:

$$\boldsymbol{c}(u_1, u_2, \dots, u_d) = \frac{1}{|R|(2\pi)^{\frac{d}{2}}} exp\left\{-\frac{1}{2}(y'R^{-1} - IR)\right\} \tag{26}$$

The Gaussian Copula is symmetric without tail dependence hence it exhibits a poor representation of extreme events.

In the case of Gaussian copula, Kendall's tau and Spearman Rho are computed respectively, as follow: $\rho\tau_{i,j} = \frac{2}{\pi} \arcsin \rho_{i,j}$ / $\rho s_{i,j} = \frac{6}{\pi} \arcsin \frac{\rho}{2}_{i,j}$

Student-t Copula

The d-dimensional Student-t copula (or briefly t copula) function is of the form:

$$\boldsymbol{C}(u_1, u_2, \dots, u_d) = T_{R,v}(T^{-1}(u_1), T^{-1}(u_2), \dots, T^{-1}(u_d)) \tag{27}$$

$$= \int_{-\infty}^{T^{-1}(u_1)} \dots \int_{-\infty}^{T^{-1}(u_d)} \frac{\Gamma\left(\frac{v+d}{2}\right)|R|^{-\frac{1}{2}}}{\Gamma\left(\frac{v}{2}\right)(v\pi)^{\frac{d}{2}}} \left(1 + \frac{1}{v} y' R^{-1} y\right)^{-\frac{v+d}{2}} dy_1 \dots dy_2$$

where $T_{R,v}$ the standardized multivariate Student-t distribution function with $m\times m$ correlation matrix R of v degrees of freedom and T^{-1} is the inverse function of the standard univariate Student-t distribution with v degrees of freedom.

The density function of the Student-t copula is given by:

$$\boldsymbol{c}(u_1, u_2, \dots, u_d) = |R|^{-\frac{1}{2}} \frac{\Gamma(\frac{v+d}{2})}{\Gamma(\frac{v}{2})} \left[\frac{\Gamma(\frac{v}{2})}{\Gamma(\frac{v+1}{2})}\right]^d \frac{\left(1+\frac{1}{v} y' R^{-1} y\right)^{-\frac{v+d}{2}}}{\prod_{i=1}^{d}\left(1+\frac{y_i^2}{v}\right)^{-\frac{v+1}{2}}} \tag{28}$$

Unlike the Gaussian Copula, the Student-t Copula is symmetric with tail dependence hence it captures extreme events.

The Kendall's tau is the same as for the Gaussian copula whereas there is no explicit form for the Spearman Rho.

The tail dependence coefficient is given by:

$$\lambda = 2T_{v+1}\left(\frac{\sqrt{v+1}\sqrt{1-\rho}}{\sqrt{1+\rho}}\right) \tag{29}$$

where T_{v+1} denotes the distribution function of a univariate Student's t-distribution with ν + 1 degrees of freedom.

3. Sample Data and Preliminary Statistics

The empirical research involves 1091 daily observations of five cryptocurrencies (Bitcoin, Dash, Ethereum, Ripple, and Monero), developed stock market indices (VIX, S&P500, NASDAQ, NIKKEI, DAX30, and FTSE), BRICS stock market indices (SSE, RTSI, BVSP, JSE 40 and BSE30), and WTI and Gold prices, sampled from 1st January 2016 to 31stMarch 2020. The database was collected from the Data Stream, Coin Market Cap and ABC bourse basis. Table 1 provides descriptive statistics for the data. All series present clear signs of non-normality. This can be seen from skewness and kurtosis. For the crypto-currencies, the skewness is positive in all cases and negative except for Bitcoin. When we consider the developed stock indices, the skewness is negative in all cases. All returns of the BRICS indices have negative skewness. For Gold and WTI, the skewness is positive and negative respectively. All returns of cryptocurrencies, developed stock market indices, and BRICS indices have kurtosis above 3. In general, the kurtosis of the cryptocurrencies is lower than the one observed in the indices. Concerning the Lagrange multiplier test, it outlines the prevalence of an ARCH effect in all the return series. As a matter of fact, the modified R/S test pertaining results attest well to the persistence of long memory with regard to the entirety of the cryptocurrency return series. Daily returns are defined by rt = (pt/pt−1), with pt standing for the data closing price on day t. Figure 2, below, illustrates the return evolution over time.

Table 1. Descriptive Statistics

Assets	Mean	Std, Dev	Skew	Kurt	JB	LM	R/S mod
VIX	0,086%	8,367%	1,522	9,490	4511,1 ***	14,354***	0,720**
Bitcoin	0,247%	4,856%	-1,031	13,012	7882,8***	4,7383***	1,761*
Dash	0,278%	7,419%	0,077	9,404	4017,4***	11,106***	2,115***
Ethereum	0,456%	7,545%	0,227	7,758	2742,6***	11,828***	1,990**
Monero	0,409%	8,390%	1,273	13,349	8387,1***	43,340***	1,837*
Ripple	0,316%	8,166%	1,760	15,942	12106***	25,340***	2,010**
Gold	0,036%	0,814%	0,121	3,529	568,28***	25,452***	1,285
WTI	-0,053%	2,679%	-1,585	26,907	33337***	92,341***	1,722
S&P500	0,023%	1,161%	-1,429	29,018	38615***	387,80***	1,279
Nasdaq	0,051%	1,333%	-1,024	16,571	12662***	336,11***	0,989
FTSE	-0,006%	1,018%	-1,567	24,591	27910***	21,352***	1,263
Nikkei	0,002%	1,251%	-0,221	7,840	2800,5***	67,055***	1,125
DAX30	-0,003%	1,185%	-1,480	22,620	23636***	14,049***	1,238
SSE	-0,017%	1,152%	-0,903	7,959	3025,2***	26,194***	1,056
RTSI	0,028%	1,580%	-1,088	11,932	6681***	24,043***	1,296
BSE30	0,013%	1,067%	-2,767	38,746	69571***	77,778***	1,413
BVSP	0,051%	1,735%	-1,621	20,498	19559***	383,47***	1,232
JSE40	-0,008%	1,193%	-1,067	12,475	7274,6***	241,83***	1,098

Source: Research finding.
Note: LM statistic is used with respect to the ARCH test, and the RS/mod statistic is used to detect long memory.
***, **, * indicate the estimators' significance at the 1%, 5% and 10% levels, respectively.

Figure 2 plots the evolution of the returns of the five selected cryptocurrencies, developed and BRICS indices, and commodities during the sample period. It is obvious that all the cryptocurrencies' returns volatility rises largely during 2017. There are three possible reasons. First, the Wanna Cry ransom ware attack in 2017 uses Bitcoin as the only payment method, and it made a natural advertisement for cryptocurrencies. Market speculation activities follow quickly. Second, numerous ICOs have launched in 2017, which raise demand and attract lots of market attention. Third, the meteoric increase of Bitcoin price as well as other cryptocurrencies in December 2017 and its coincidence with the initiation of Bitcoin futures by the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) increased the cryptocurrencies' volatilities. However, the evolution of these currencies becomes more volatile in the period of the COVID-19 pandemic. In fact, the pandemic has managed to plunder and destabilize the world in just the last few months, putting in danger not only lives, but economic boundaries, well-established global businesses, and the very essence of the world's financial system. Regarding commodities, the evolution is not very volatile during the period study and suddenly during the pandemic, the evolution becomes more volatile. Moreover, the onset of the COVID-19 pandemic and its global spread has resulted in a fall in oil prices due to subdued demand foreseen and the price war between Russia and Saudi Arabia. The prices recovered, however, partially after hopes for an agreement between Russia and OPEC increased. Regarding the evolution of the indices, the evolution becomes more volatile during the pandemic. The most attractive return volatility is for the WTI evolution. One important impact of the coronavirus outbreak on the downstream oil industry is that the price of crude oil has fallen significantly in a short time, taking billions off the stock prices of major oil and gas companies. The benchmark West Texas Intermediate (WTI) crude oil price reached a low of $22.39 per barrel on 20 March 2020. This was less than half the price compared to the beginning of the month.

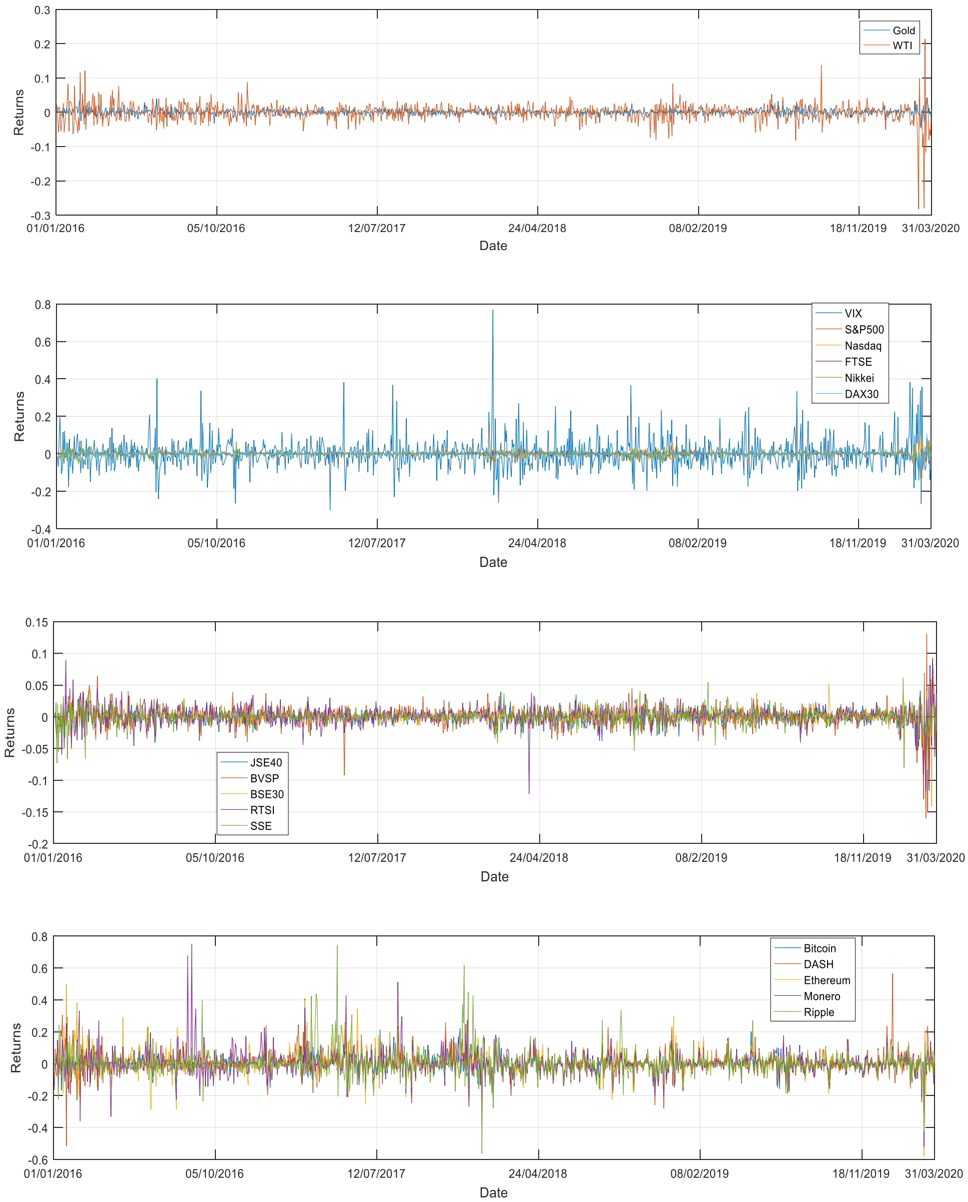


Figure 2. Price Returns Evolution
Source: Research finding.

4. Empirical Results

4.1 Marginal Model Results

The best specification of the marginal model is of primary interest in this section in order to avoid biased copula estimations. We consider a battery of GARCH family models with different return distributions (Gauss, Student, skewed-Student, GED).

Investigating the volatility of returns is important in terms of financial investment like hedging or pricing instruments. Therefore, these results would be particularly useful in terms of portfolio and risk management and could help others make better informed decisions with regard to financial investments and the potential benefits and pitfalls of utilizing Cryptocurrencies, Gold and Oil.

For all return series, we find that the Skewed-Student is the most appropriate distribution based on LL, AIC, and BIC criteria (Table 2). As can be noticed from Table 4, the AIC and BIC information criteria associated values are discovered to be minimized, and the log-likelihood (LL) value maximized under the AR(1)-EGARCH(1,1) model with a skewed-t distribution with regard to the VIX return-volatility series. Indeed, the three information criteria (AIC, BIC, LL) are also best fit to be opted for by means of the AR(1)-HYGARCH(1,1,1) model under skewed-t error distribution, concerning the Dash, Ethereum, Monero, S&P500, WTI, Nasdaq, FTSE, DAX30, SSE, Nikkei, BSE30, and JSE 40 relevant return series, while the Gold, RTSI, and BVSP returns are more appropriately fit to be modulated through an AR(1)-GARCH(1,1) under skewed-t distribution, and, finally, the AR(1)-FIGARCH(1,1,1) under skewed-t distribution proves to stand as the best appropriate tool fit to describe the Ripple and Bitcoin returns related volatility.

Table 2. Summary of the Selected Models

Assets	Model	Distribution
VIX	EGARCH	Skewed-t
Bitcoin	FIGARCH	Skewed-t
Dash	HYGARCH	Skewed-t
Etherreum	HYGARCH	Skewed-t
Monero	HYGARCH	Skewed-t
Ripple	FIGARCH	Skewed-t
Gold	GARCH	Skewed-t
WTI	HYGARCH	Skewed-t
SP500	HYGARCH	Skewed-t
Nasdaq	HYGARCH	Skewed-t
FTSE	HYGARCH	Skewed-t
Nikkei	HYGARCH	Skewed-t
DAX30	HYGARCH	Skewed-t
SSE	HYGARCH	Skewed-t
RTSI	GARCH	Skewed-t
BSE30	HYGARCH	Skewed-t
BVSP	GARCH	Skewed-t

JSE40	HYGARCH	Skewed-t

Source: Research finding.

Gleaning information from Table 3, the parameter estimation for the different GARCH models shows that the positive and significant coefficients of the GARCH term (β1) except for Ethereum, Monero, Ripple, Nikkei, and WTI, clearly shows that stock market news about past volatility has explanatory power on current volatility.

Table 3. GARCH Estimation Models

Bitcoin	Dash	Ether	Monero	Ripple	VIX	SP500	Nasdaq	FTSE	Nikkei	DAX 30	SSE	RTSI	BSE30	BVSP	JSE40	Gold	WTI
0,002**	-0,001	0,002	0,002	-0,002	0,005**	0,001***	0,001***	0,0002	0,0004	0,0003	0,0002	0,001	0,001**	0,001***	0,0002	0,0002	0,0001
-0,021	-0,017	-0,025	-0,066	-0,129	-0,047	-0,078	-0,086	0,005	0,010	-0,010	-0,014	0,037	0,054	-0,031	0,021	-0,031	-0,024
0,219	4,777	27,601	7,426	6,950	-4,516	0,026	0,035	0,045**	0,290**	0,084	0,007	0,027	0,030	0,081	0,077	0,783	0,147
-0,020	-0,038	-0,582	0,037	-0,315	0,496	0,063	0,082	0,241**	-0,237	0,088	-0,012	0,076***	0,095	0,088***	0,097	0,041***	0,256
0,903***	0,423**	-0,674	0,298	-0,268	0,899***	0,562***	0,691***	0,695***	0,089	0,463***	0,950***	0,913***	0,834***	0,876 ***	0,599***	0,947***	0,809
/	/	/	/	/	0,218***	/	/	/	/	/	/	/	/	/	/	/	/
/	/	/	/	/	0,065**	/	/	/	/	/	/	/	/	/	/	/	/
1,105***	0,589***	0,312**	0,421**	0,326***	/	0,687***	0,776***	0,733***	0,576***	0,506**	1,072***	/	0,850 ***	/	0,597***	/	0,667***
-0,025	0,014	0,070	0,058	0,057	0,314***	-0,075	-0,126	-0,112	-0,055	-0,106	-0,069	-0,141 ***	-0,016	-0,069	-0,109***	-0,011	-0,122
3,062***	2,908***	2,372***	2,815***	2,936***	4,389***	4,247	4,133***	6,039***	3,634***	4,297***	3,535***	7,015***	5,237***	5,400***	8,061***	5,788	5,075***
/	0,144	0,805	0,222	/	/	0,028	0,028	-0,063	-0,032	0,004	0,0001	/	-0,036	/	-0,057	/	-0,028

Source: Research finding.

Note: ***, **, * indicate that the estimators are significant at the 1%, 5% and 10% levels, respectively.

Table 4. Goodness-of-Fit Estimation Relevant to the Different GARCH-Family Models

Assets		**AR-GARCH**	**AR-EGARCH**	**AR-FIGARCH**	**AR-HYGARCH**
VIX	LL	1359,597	1388,603	1360,458	1361,418
	BIC	-2,450	-2,490	-2,445	-2,440
	AIC	-2,482	-2,531	-2,482	-2,482
Bitcoin	LL	2045,730	2035,929	2053,817	2049,711
	BIC	-3,709	-3,684	-3,711	-3,703
	AIC	-3,741	-3,721	-3,752	-3,744
Dash	LL	1540,555	1537,164	1541,592	1542,260
	BIC	-2,782	-2,763	-2,777	-2,772
	AIC	-2,814	-2,804	-2,814	-2,813
Ethereum	LL	1496,883	1495,385	1496,422	1498,918
	BIC	-2,702	-2,686	-2,694	-2,693
	AIC	-2,734	-2,727	-2,731	-2,734
Monero	LL	1384,030	1381,238	1386,410	1387,113
	BIC	-2,495	-2,477	-2,493	-2,487
	AIC	-2,527	-2,518	-2,529	-2,529
Ripple	LL	1593,662	1598,744	1605,725	1598,472
	BIC	-2,879	-2,876	-2,889	-2,882
	AIC	-2,911	-2,917	-2,930	-2,918
Gold	LL	3800,107	3723,260	3800,830	3800,830
	BIC	-6,928	-6,774	-6,923	-6,916
	AIC	-6,960	-6,815	-6,959	-6,958
WTI	LL	2702,186	2659,750	2704,541	2704,802
	BIC	-4,913	-4,823	-4,911	-4,905
	AIC	-4,945	-4,864	-4,948	-4,946
SP500	LL	3895,304	3891,349	3896,746	3896,857
	BIC	-7,102	-7,082	-7,099	-7,092
	AIC	-7,135	-7,124	-7,135	-7,134
Nasdaq	LL	3575,279	3570,312	3575,727	3575,919
	BIC	-6,515	-6,493	-6,510	-6,504
	AIC	-6,547	-6,535	-6,546	-6,545

FTSE	LL	3772,863	3765,995	3774,510	3775,133
	BIC	-6,878	-6,852	-6,874	-6,869
	AIC	-6,910	-6,894	-6,911	-6,910
Nikkei	LL	3481,474	3484,129	3484,094	3487,862
	BIC	-6,343	-6,335	-6,342	-6,342
	AIC	-6,375	-6,376	-6,378	-6,383
DAX 30	LL	3558,646	3560,380	3560,379	3570,891
	BIC	-6,485	-6,475	-6,482	-6,494
	AIC	-6,517	-6,516	-6,518	-6,536
SSE	LL	3582,792	3572,595	3583,308	3583,308
	BIC	-6,529	-6,498	-6,524	-6,517
	AIC	-6,561	-6,539	-6,560	-6,558
RTSI	LL	3235,069	3170,950	3227,672	3233,374
	BIC	-5,885	-5,761	-5,877	-5,875
	AIC	-5,921	-5,802	-5,910	-5,916
BSE30	LL	3755,925	3750,272	3755,701	3756,189
	BIC	-6,847	-6,824	-6,840	-6,834
	AIC	-6,879	-6,865	-6,877	-6,876
BVSP	LL	3177,804	3160,533	3173,732	3174,225
	BIC	-5,773	-5,741	-5,772	-5,779
	AIC	-5,814	-5,783	-5,809	-5,811
JSE40	LL	3512,059	3498,939	3513,308	3513,542
	BIC	-6,399	-6,362	-6,395	-6,389
	AIC	-6,431	-6,404	-6,432	-6,430

Source: Research finding.

The fractionally integrated parameter (d-FIGARCH) values are positive and statistically significant for all series, highlighting the presence of long memory in variance. The Bitcoin, SSE, and BSE30 are the highest persistent series, while the Ripple and Ethereum are the least persistent series. The asymmetry parameter is significant for a few cases (VIX, RTSI, and JSE40). In addition, the tail parameter is statistically significant, suggesting the appropriateness of the skewed-student-t distribution. The positive and significant leverage effect parameter in the EGARCH (1,1) model indicates that positive shocks (good news) increase volatility more than negative shocks (bad news) of the same sign. This result is confirmed by Fakhfekh and Jeribi (2020).

4.2 Results and Discussion

We are seeking to study the role of cryptocurrencies as a hedge and safe haven against conventional assets applying the categorizations of Baur and Lucey (2010). Therefore, to distinguish between these features, we employ the C-vine copula with time-varying pair copula construction theory to study the dependence structure between cryptocurrencies and conventional assets. The use of copulas is very crucial since it gives us information about the dependence on average and the dependence in times of extreme market movements. On one hand, the dynamic dependence on average is given by Kendall's tau which is obtained from the dependence parameter of the copula. In fact, the dependence on average and the dependence in turbulent periods let us know, respectively, about the hedge and safe haven properties.

In this part, we performed the Copulas approach to test whether these pairs of cryptocurrencies and conventional assets have a dependence structure at the tail or not. Hence, our work tests two types of Copulas Gaussian (Normal) and t-Copulas (t-student Copulas) for the dependence structure of these cryptocurrencies. Malevergne and Sornette (2003) also indicated that the Copulas approaches (including Gaussian and the Student's-t) are taken into consideration for testing correlation in terms of structural dependence among currencies.

We select the structure of the C-vine with the empirical Kendall's tau correlation of the marginal models. The idea is to rank pairs of series from the highest to the lowest Kendall's tau correlation. Once a series has been selected twice, it cannot be used to form new pairs.

Our findings (Table 5) demonstrated that cryptocurrencies have a weak dependence structure on Gaussian Copulas, which should be referred to the Student-t one. Based on the AIC results, we came to the conclusion that the Gaussian is a better fit for our data than its counterpart. Indeed, the time-varying copula outperforms the static copula since for all pairs the time-varying copula was selected based on the (LL) criterion.

Although, the selected cryptocurrencies have different advantages and characteristics that lead to different demands and sources of risks. Bitcoin is the first, most famous, and largest-capped cryptocurrency; it is a preferred tool for cross-border transactions and blackmailing payment, for example, the notorious WannaCry ransomware attack in 2017 used Bitcoin as the only way to pay the ransom. Ethereum is remarked as an archetype of 'Blockchain 2.0' for its programmability, or in other words, smart contract; it enables multiple parties to freely define their trading logic and trade on the blockchain with fairness; Ethereum provides an efficient platform for conveniently raising funds (i.e. initial coin offering, ICO) and it also acts as the funding currency of ICO. Ripple is a centrally controlled cryptocurrency and is welcomed for its good liquidity, Ripple features fast payment and low transaction fees, and it also has got some support from traditional banks and financial institutions. Dash and Monero are famous for good anonymity. We observe that the dependence parameter is awfully volatile and alternates between positive and negative values (Fig.3). In fact, when looking into the behavior of the relationships between the Nasdaq-Digital pair, we observe that the Monero, Ethereum, and Dash share the same behavior of dependence over time. Moreover, when looking into the behavior of the relationships, we observe that during the COVID-19 pandemic the average of dependence is negative and reaches -0.15 which means that these cryptocurrencies act as a safe haven for the Nasdaq index. However, in consistence with Jeribi and Snene_Manzli (2021), Ripple differs in terms of the type of dependence, in which the parameter of dependence is positive during the period study proving the role of the Ripple as a diversifier. The results show evidence of structural breaks existence in the returns of all pairs without any exception such as the case in Ardia et al. (2019)'s study. As for the relationship between Ethereum-FTSE the first change occurs in May 2016 where the relationship decreases almost to -0.25. The main event registered in May 2016, is the crowdfunding campaign using Ethereum of the Decentralized autonomous organization (DAO), which set the record for the largest crowdfunding campaign in history with 120 Million USD worth of Ether raised. Toward the end of the investigated period, which coincides with the COVID-19 pandemic, we see an increase in the degree of dependence. Regarding the two pairs Dash-FTSE and Ripple-FTSE the dependence is usually positive. However, during the COVID-19 pandemic, the behavior is different. In fact, concerning the first pair, the dependence increase and reaches 0.1; then in the second, pair the dependence decrease and reaches 0.03. The dynamic dependence between digital currencies (Bitcoin, Dash, Ripple, and Ethereum) and the S&P500 index is alternating between positive and negative values. Precisely, during the COVID-19 pandemic, the co-movement becomes positive. On the Monero currency side, the behavior is opposite, usually positive, and rises in the COVID-19 pandemic. For the pair Ripple-DAX30, the dependence dropped to negative and reached -0.05 during the COVID-19 pandemic confirming the role of the Ripple as a safe haven asset. Indeed, based on the dependence pattern, we observe that the dependence between Bitcoin-DAX30 and Ethereum-DAX30 during March 2018 shows a co-movement with lower volatility than the period prior to March 2018. Regarding the Nikkei index, the dependence dynamic with Bitcoin and Ripple shares the same behavior, altering between positive and negative values with an increase in the pandemic. For Ethereum the case is different, the dependence is negative during the period of study except during the pandemic with an increase to positive dependence confirming the role of diversifier asset. The behavior of the Dash and

Monero is different and dropped to negative (-0.05) in the pandemic which proves the role of safe haven of this asset. This result is inconsistent with Jeribi and Snene_Manzli (2021) and Jeribi et al. (2020) who find out that Dash and Monero acted as diversifiers during the pandemic. The dependence between Ethereum, Monero, Bitcoin, and Dash against VIX share common features and drop to negative in the pandemic period (Baur et al., 2017). Bitcoin is thereby found to possess some of the same hedging abilities as gold and can be included in the variety of tools available to market analysts to hedge market-specific risk (Dyhrberg, 2016). This result is inconsistent with Klein et al. (2018) and Jeribi and Snene_Manzli (2021); however, it is consistent with Bouri et al. (2020) who concluded that Bitcoin should be used as a modern virtual gold since it has some of the virtuosity of gold against the extreme downturn of stock market indices. Turning to Ripple, the dependence moves from negative with a -0.05 value to positive and reaches 0.05.

Table 5. C-vine Dependence Results between Developed Stock Market Indices and Cryptocurrencies

Pair	Family	θ	N	LL	W	α	β	LL
Tree 1								
3,1	T	-0.72	11.19	396.76	-2,064	0.54	-0.97	**405.06**
3,7	T	0.01	16.30	1.86	0.032	0.20	-0.41	1.31
3,5	T	0.14	14.70	12.62	0.21	-0.09	0.62	11.85
3,6	T	0.52	6.27	178.46	1.15	-0.003	-0.016	166.56
3,8	N	0.05		1.23	0.10	-0.33	0.15	**2.50**
3,2	T	0.67	2.00	357.83	0.15	0.94	1.53	**469.81**
3,4	T	0.37	5.92	89.93	0.05	0.15	1.84	96.35
3,9	N	0.05		1.29	0.16	0.57	-1.94	**3.62**
3,1	N	0.04		0.85	0.08	-0.35	0.13	**2.38**
11,3	N	0.03		0.421	0.04	-0.01	0.25	**0.423**
Tree 2								
10,1;3	N	0.01		0.13	-0.05	0.15	-1.64	**0.28**
10,7;3	T	0.43	3.84	132.54	0.05	0.21	1.81	**138.05**
10,5;3	N	0.03		0.59	0.10	-0.19	-0.95	**0.81**
10,6;3	N	0.05		2.53	0.08	-0.06	0.9	**2.68**
10,8;3	T	0.59	2.26	290.40	0.10	0.45	1.75	**293.85**
10,2;3	N	0.00		0.19	0.04	0.07	-0.63	**0.24**
10,4;3	T	0.04	14.26	3.17	0.008	0.019	1.8	2.20
10,9;3	T	0.46	3.76	152.86	0.20	0.21	1.49	136.43
11,10;3	T	0.54	3.61	202.16	0.19	0.53	1.35	**215.82**
Tree 3								
9,1;10,3	N	-0.01		0.67	-0.06	0.41	0.08	**3.24**
9,7;10,3	t	0.50	2.81	286.42	0.18	0.57	1.48	**290.23**
9,5;10,3	N	-0.08		1.32	-0.08	0.26	-0.06	**2.60**
9,6;10,3	N	-0.03		0.26	0.006	0.05	1.73	**1.67**
9,8;10,3	t	0.32		174.09	0.71	0.41	0.27	161.54
9,2;10,3	N	-0.01		0.08	0.006	0.70	-1.23	**3.58**
9,4;10,3	N	-0.02		0.07	0.006	0.09	1.63	**3.29**
11,9;10,3	t	0.23	7.51	114.91	0.12	0.32	1.50	**125.24**
Tree 4								

4,1;9,10,3	N	-0.12		65.50	-0.43	0.44	0.42	**71.36**
4,7;9,10,3	N	-0.02		1.32e-4	7.5e-4	0.052	1.72	**0.85**
4,5;9,10,3	t	0.14	14.68	22.87	0.017	0.04	1.88	**24.25**
4,6;9,10,3	t	0.47	7.64	219.04	0.18	0.59	1.41	**268.82**
4,8;9,10,3	N	0.01		0.71	0.09	0.12	-0.96	**0.86**
4,2;9,10,3	t	0.29	10.67	128.63	0.24	0.32	1.27	**139.22**
11,4;9,10,3	N	0.07		3.57	0.08	-0.04	0.98	**3.68**
Tree 5								
2,1;4,9,10,3	t	-0.18	10.92	208.64	-0.08	0.53	1.73	**276.15**
2,7;4,9,10,3	N	-0.02		0.20	-0.06	0.39	-1.61	**1.26**
2,5;4,9,10,3	N	0.05		14.69	0.33	-0.03	0.02	**14.71**
2,6;4,9,10,3	N	0.07		114.07	0.07	0.32	1.75	**145.03**
2,8;4,9,10,3	N	-0.01		0.33	0.06	0.46	-1.99	**1.73**
11,2;4,9,10,3	N	-0.11		0.87	-0.14	0.51	-2	**3.04**
Tree 6								
8,1;2,4,9,10,3	N	-0.05		1.42	-0.18	0.46	-1.93	**2.63**
8,7;2,4,9,10,3	t	0.08	8.78	122.62	0.39	0.68	0.35	121.98
8,5;2,4,9,10,3	N	0.01		0.05	0.035	-0.51	-0.7	**2.08**
8,6;2,4,9,10,3	N	0.02		2.21	0.20	-.09	-1.13	**2.25**
11,8;2,4,9,10,3	t	0.20	10.12	178.90	0.09	0.41	1.68	**205.91**
Tree 7								
6,1;8,2,4,9,10,3	N	-0.14		141.48	-1.54	0.03	-1.07	**141.51**
6,7;8,2,4,9,10,3	N	0.03		0.49	0.007	0.07	1.72	**2.28**
6,5;8,2,4,9,10,3	t	0.07	14.59	30.05	0.002	0.033	1.99	29.60
11,6;8,2,4,9,10,3	N	0.04		3.45	0.12	-0.14	0.61	**3.92**
5,1;6,8,2,4,9,10,3	N	0.01		7.31	-0.02	-0.05	1.90	**9.91**
Tree 8								
5,7;6,8,2,4,9,10,3	N	0.02		0.01	-0.006	0.10	1.12	**0.9**
11,5;6,8,2,4,9,10,3	N	-0.03		0.08	-0.002	0.04	1.79	**1.15**
Tree 9								
11,1;5,6,8,2,4,9,10,3	N	-0.02		0.48	-0.02	-0.07	1.35	**0.88**
11,7;5,6,8,2,4,9,10,3	t	0.02	10.64	77.44	0.29	0.55	0.65	**92.22**
Tree 10								
7,1;11,5,6,8,2,4,9,10,3	N	-0.01		0.11	-0,002	0,05	1.78	**1,6**

Source: Research finding.

Note: 1 <-> VIX, 2 <-> SP500, 3 <-> Nasdaq, 4 <-> FTSE, 5 <-> Nikkei, 6 <-> DAX.30, 7 <-> Bitcoin, 8 <-> Dash, 9 <-> Ethereum, 10 <-> Monero, 11 <-> Ripple.

Table 6. C-vine Dependence Results between BRICS Indices and Cryptocurrencies

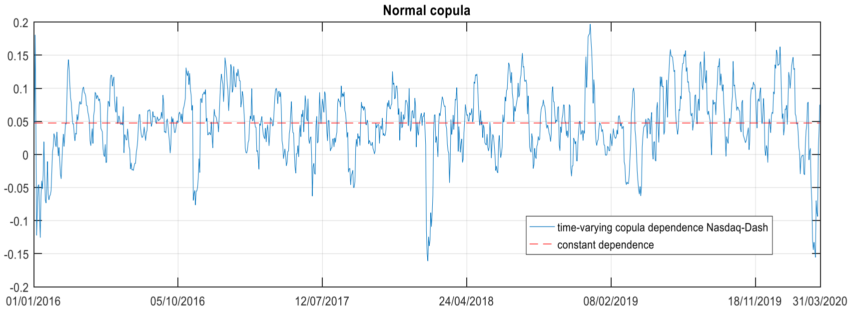
Pair	Family	θ	N	LL	W	α	β	LL
Tree 1								
9,4	t	0.05	20.46	2.68	0.06	0.07	0.68	2.22
9,6	t	0.43	3.92	132.54	0.05	0.21	1.81	**138.05**
9,1	t	0.06	14.89	3.42	0.01	0.025	1.77	**2.63**
9,2	t	0.07	19.91	3.98	0.12	0.28	-0.06	**5.21**
9,7	t	0.59	2.24	290.40	0.10	0.45	1.75	**293.85**
9,3	t	-0.03	12.19	4.07	-0.16	0.34	-2,02	**4.19**
9,8	t	0.46	3.73	152.86	0.20	0.21	1.49	136.43
9,5	t	0.07	17.20	4.29	0.02	-0.03	1.66	3.88
10,9	t	0.54	3.61	202.16	0.19	0.53	1.35	**215.82**
Tree 2								
5,4;9	N	0.26		38.81	-0.002	0.03	2.02	**40.75**
5,6;9	N	-0.01		0.92	0.15	-0.23	-1.16	**1.24**
5,1;9	t	0.26		41.35	0.09	0.07	1.59	41.11
5,2;9	t	0.41		99.52	0.08	0.11	1.79	**103.91**
5,7;9	N	0.04		4.35	0.23	-0.16	-0.36	**4.63**
5,3;9	t	0.39		92.39	-0.02	0.06	2.10	**97.19**
5,8;9	N	-0.02		0.36	0.04	0.01	0.32	0.36
10,5;9	N	0.03		2.47	0.06	-0.11	1.13	**3.25**
Tree 3								
8,4;5,9	N	-0.02		0.03	0.01	0.20	0.24	**0.93**
8,6;5,9	t	0.50	2.83	280.42	0.18	0.57	1.48	**290.23**
8,1;5,9	N	0.03		0.86	0.006	0.07	1.81	**4.66**
8,2;5,9	N	0.00		0.54	0.0016	0,017	1.98	**3.91**
8,7;5,9	t	0.32	10.21	174.09	0.71	0.41	0.27	161.54
8,3;5,9	N	-0.03		0.87	-0.007	-0.008	1.74	**4.78**
10,8;5,9	t	0.23	7.62	114.91	0.12	0.32	1.50	**125.24**
Tree 4								
3,4;8,5,9	N	0.12		24.45	0.26	0.15	0.61	**25.51**
3,6;8,5,9	N	-0.02		0.32	-0.02	0.06	0.78	**0.51**
3,1;8,5,9	N	0.14		27.73	0.13	0.07	1.33	**28.43**
3,2;8,5,9		N	0.13	38.49	0.08	0.11	1.62	**42.86**
3,7;8,5,9	t	-0.04	21.19	5.22	-0.11	-0.06	-1.46	1.54
10,3;8,5,9	N	-0.03		0.51	-0.02	0.04	1.10	**0.63**
Tree 5								
7,4;3,8,5,9	N	-0.01		0,26	0.002	0.03	1.78	**0.84**
7,6;3,8,5,9	t	0.07	8.67	122.62	0.39	0.68	0.35	121.98
7,1;3,8,5,9	N	-0.09		0.08	-0.03	-0.18	-0.72	**0.42**
7,2;3,8,5,9		N	0.02	2.39	0.10	0.20	0.23	**3.34**
10,7;3,8,5,9	t	0.19	10.06	178.90	0.09	0.41	1.68	**205.91**
Tree 6								
2,4;7,3,8,5,9	t	0.24	11.94	64.40	0.26	0.18	1.05	**65.80**
2,6;7,3,8,5,9	N	-0.00		0.89	0.16	-0.53	-1.16	**2.56**
2,1;7,3,8,5,9	t	0.05	18.05	18.92	0.71	-0.38	-1.82	18.84
10,2;7,3,8,5,9	N	-0.00		1.21	0.02	0.12	1.30	**2.60**
Tree 7								
1,4;2,7,3,8,5,9	N	0.01		6.52	0.43	-0.48	-1.83	**8.50**
1,6;2,7,3,8,5,9	N	-0.05		6.7e-4	9.22e-4	0.06	1.84	**4.60**
10,1;2,7,3,8,5,9	N	-0.03		0.01	0.02	-0.31	0.33	**1.41**

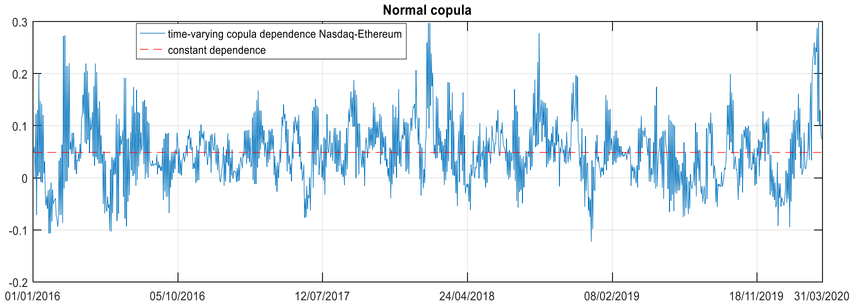
Tree 8								
10,4;1,2,7,3,8,5,9	N	-0.01		0.33	0.07	0.27	-1.67	**0.76**
10,6;1,2,7,3,8,5,9	t	0.02	11.86	77.44	0.29	0.55	-1.67	**92.22**
Tree 9								
6,4;10,1,2,7,3,8,5,9	N	-0.02		0.07	0.01	0,02	0,94	**0,09**

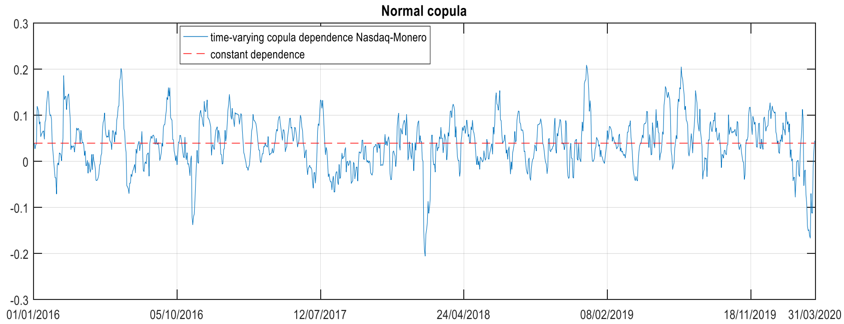
Source: Research finding.

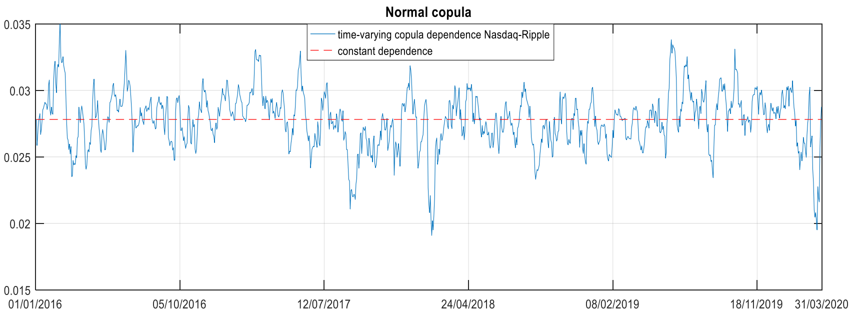
Note: 1 <-> SSE, 2 <-> RTSI, 3 <-> BSE.30, 4 <-> BVSP, 5 <-> JSE.40, 6 <-> Bitcoin, 7 <-> Dash, 8 <-> Ethereum, 9 <-> Monero, 10 <-> Ripple.

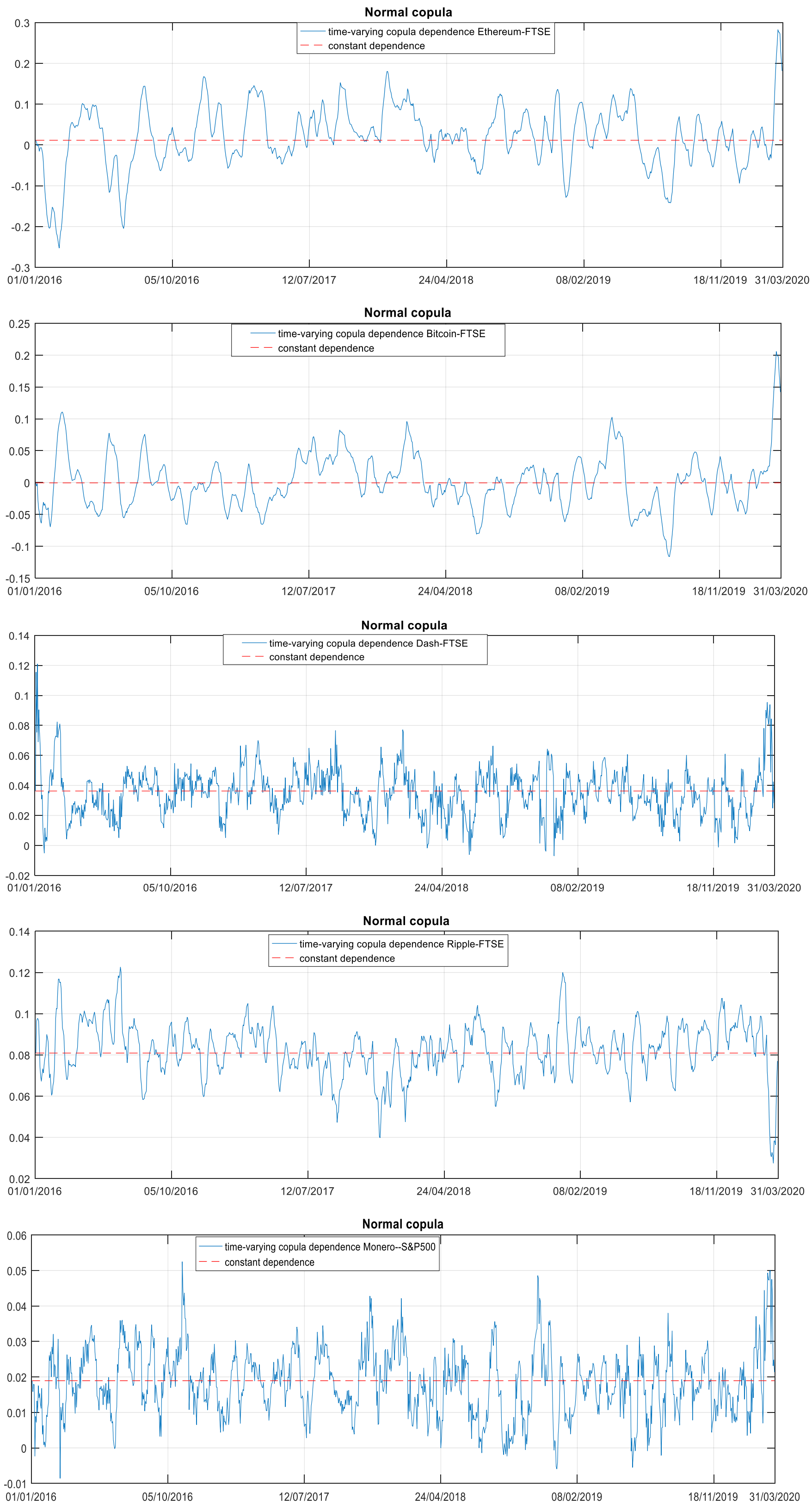
Like before, the Student-t copula is only selected in the first tree (Table 6). At the BRICS and digital currencies dynamic dependence (Figure 4), results show that the dependence between the pair JSE40-Bitcoin is usually positive except during March 2018 and the covid19 pandemic which drop to negative and reach (-0.1) confirming the role of Bitcoin as a safe haven asset. In fact, Bitcoin prices increased significantly during the second half of 2017 and decreased significantly by the beginning of 2018. Bitcoin prices increased from 1,000$ in early 2017 to over 19,000$ by mid-December, market rumors were that Bitcoin usurped Gold's position as a store of value and an alternative to fiat currencies. The case is not similar for the Dash and Ethereum, which act as diversifiers during the period study. These results are consistent with Corbet et al. (2018), Jeribi and Ghorbel (2021), and Jeribi and Fakhfekh (2021). A mixed picture is shown that Ripple act as a diversifier between 2016 and 2019 and a safe haven during the COVID-19 pandemic.

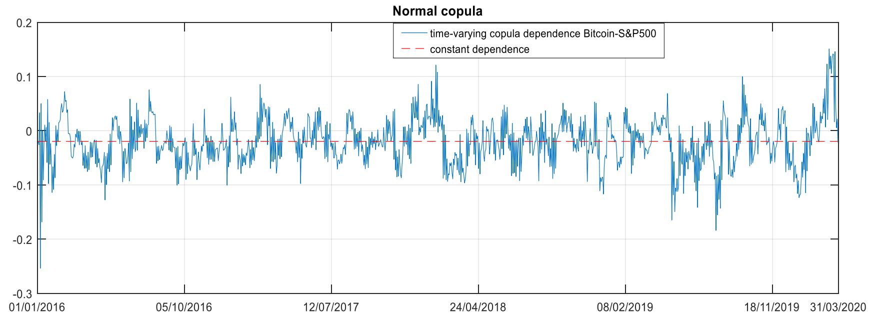

Normal copula
time-varying copula dependence Nasdaq-Dash
constant dependence
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

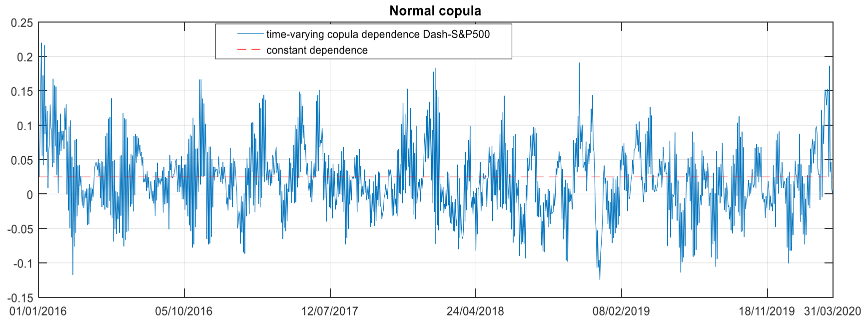

Normal copula
time-varying copula dependence Nasdaq-Ethereum
constant dependence
0.3
0.2
0.1
0
-0.1
-0.2
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

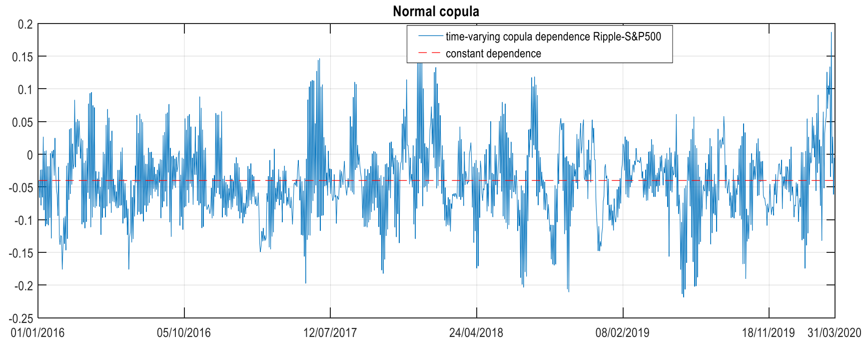

Normal copula
time-varying copula dependence Nasdaq-Monero
constant dependence
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

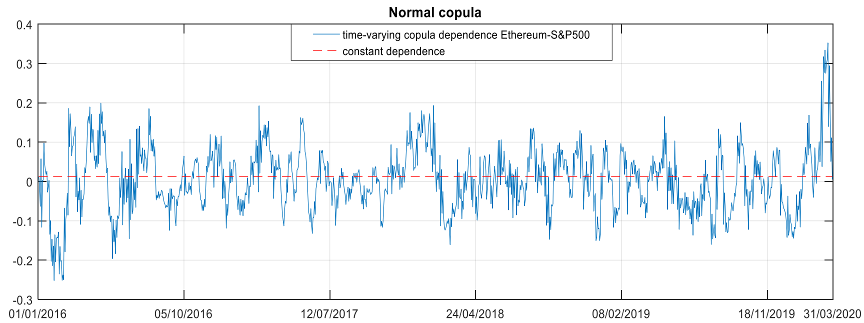

Normal copula
time-varying copula dependence Nasdaq-Ripple
constant dependence
0.035
0.03
0.025
0.02
0.015
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

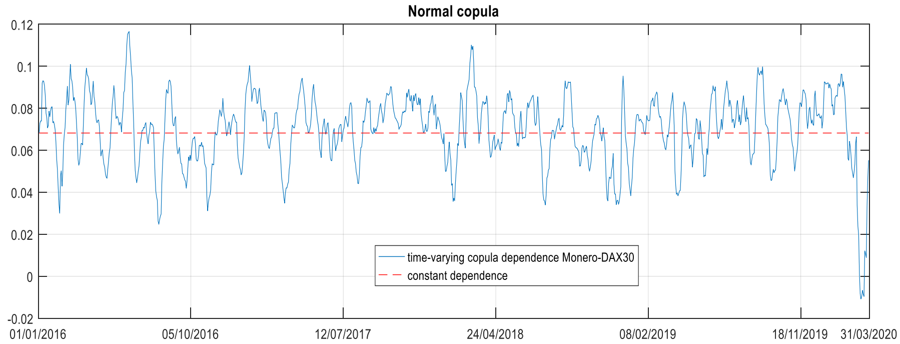

Normal copula
time-varying copula dependence Ethereum-FTSE
constant dependence
Normal copula
time-varying copula dependence Bitcoin-FTSE
constant dependence
Normal copula
time-varying copula dependence Dash-FTSE
constant dependence
Normal copula
time-varying copula dependence Ripple-FTSE
constant dependence
Normal copula
time-varying copula dependence Monero--S&P500
constant dependence
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

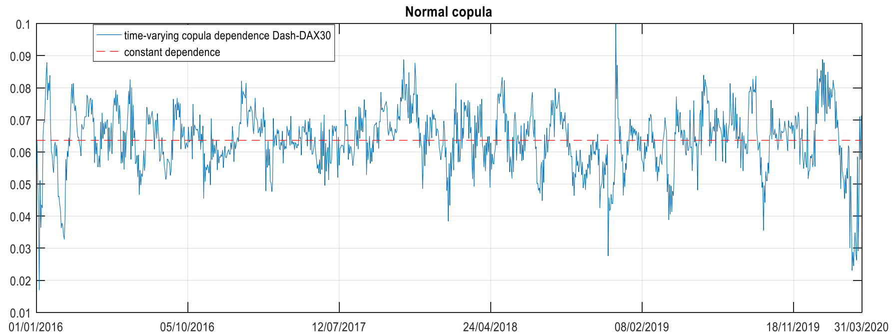

Normal copula
time-varying copula dependence Bitcoin-S&P500
constant dependence
0.2
0.1
0
-0.1
-0.2
-0.3
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

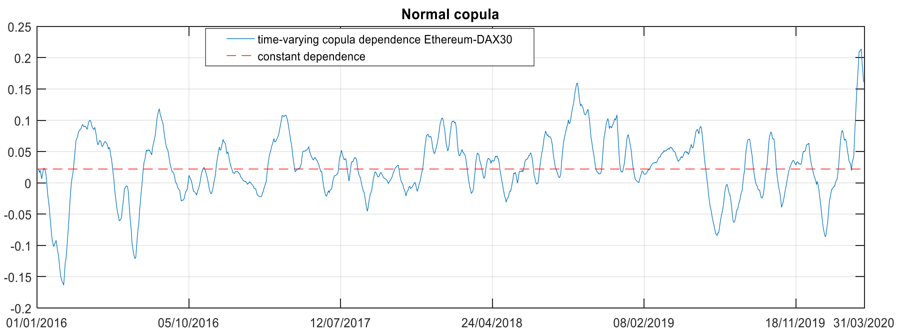

Normal copula
time-varying copula dependence Dash-S&P500
constant dependence
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

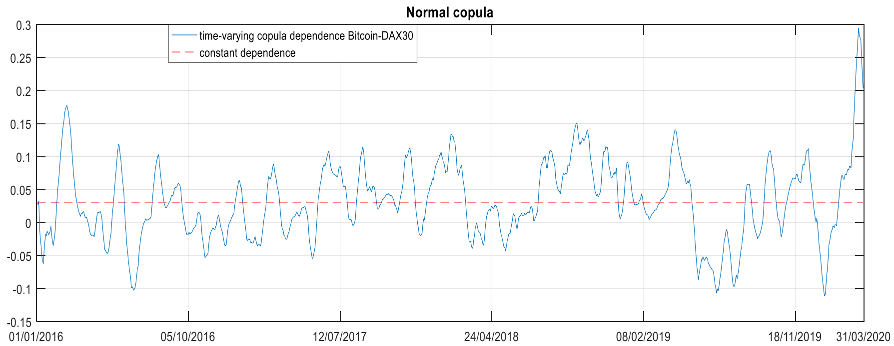

Normal copula
time-varying copula dependence Ripple-S&P500
constant dependence
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

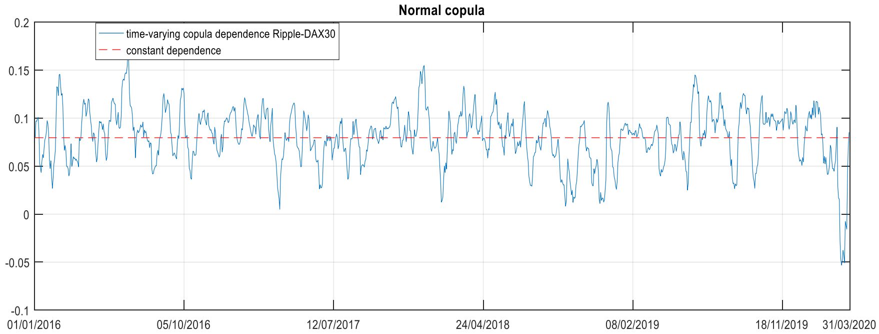

Normal copula
time-varying copula dependence Ethereum-S&P500
constant dependence
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

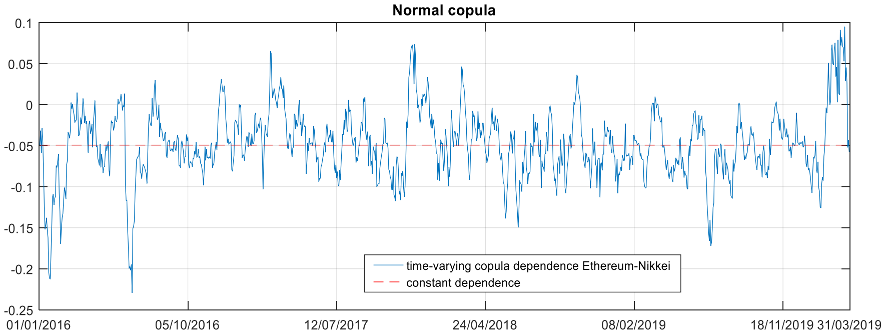

Normal copula
time-varying copula dependence Monero-DAX30
constant dependence
0.12
0.1
0.08
0.06
0.04
0.02
0
-0.02
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

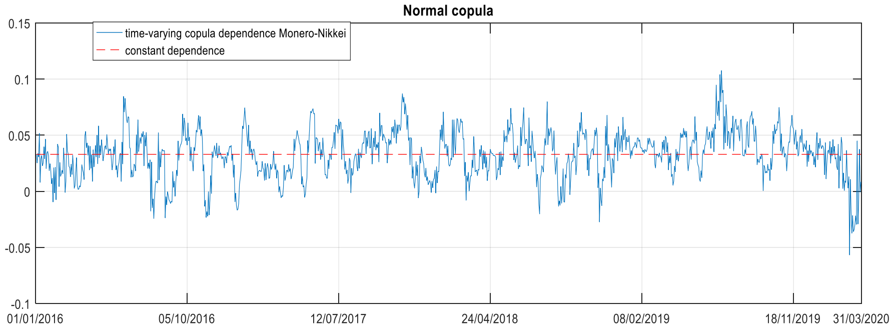

Normal copula
time-varying copula dependence Dash-DAX30
constant dependence
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

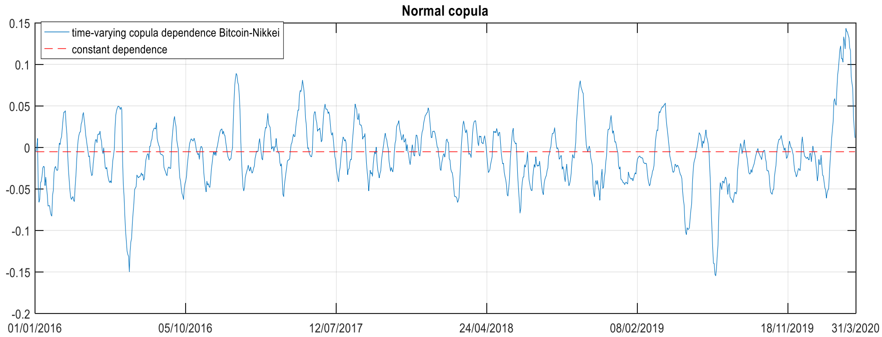

Normal copula
time-varying copula dependence Ethereum-DAX30
constant dependence
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

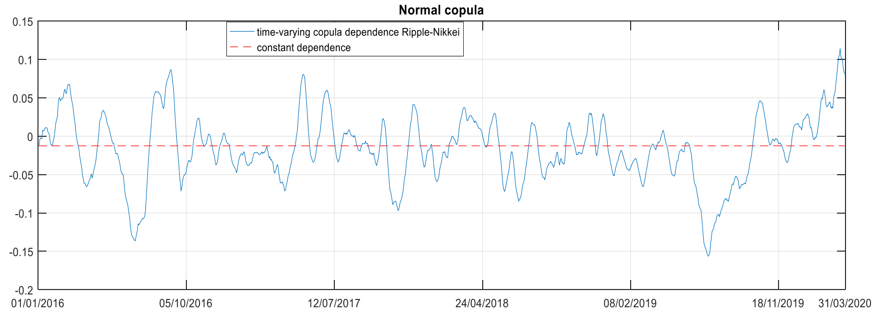

Normal copula
time-varying copula dependence Bitcoin-DAX30
constant dependence
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

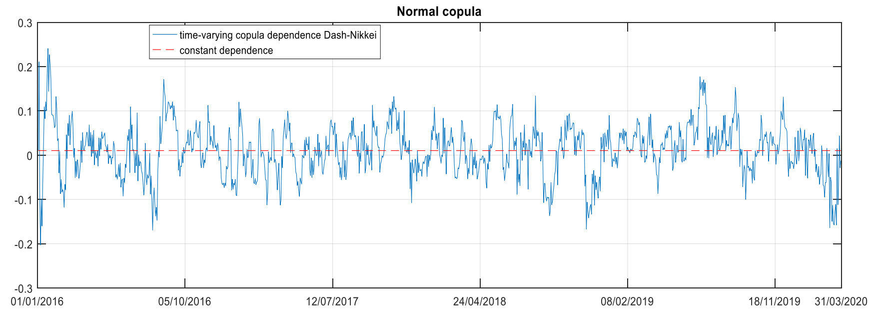

Normal copula
time-varying copula dependence Ripple-DAX30
constant dependence
0.2
0.15
0.1
0.05
0
-0.05
-0.1
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

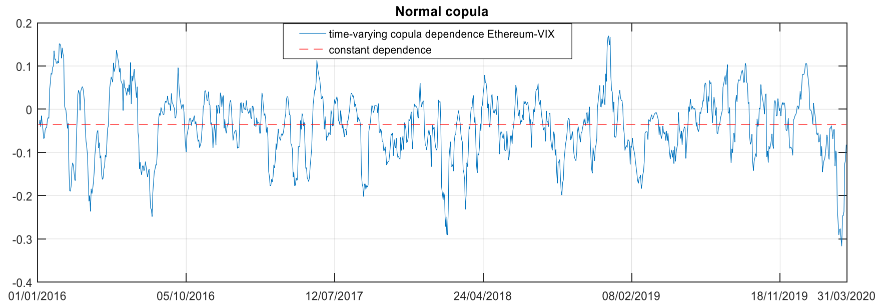

Normal copula
time-varying copula dependence Ethereum-Nikkei
constant dependence
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019 31/03/2019

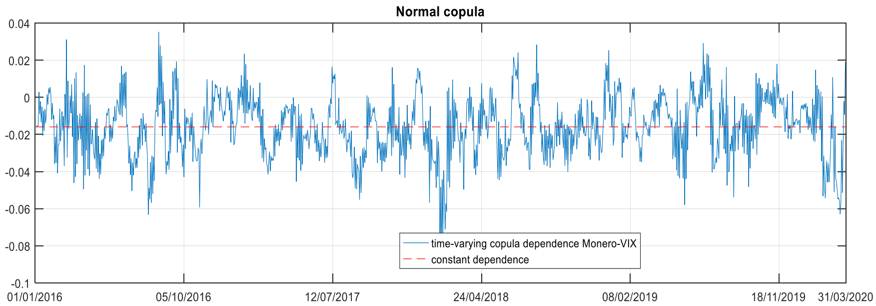

Normal copula
time-varying copula dependence Monero-Nikkei
constant dependence
0.15
0.1
0.05
0
-0.05
-0.1
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

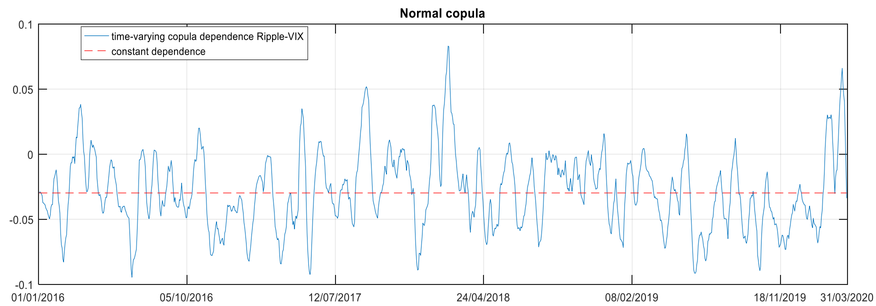

Normal copula
time-varying copula dependence Bitcoin-Nikkei
constant dependence
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/3/2020


Normal copula
time-varying copula dependence Ripple-Nikkei
constant dependence
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020


Normal copula
time-varying copula dependence Dash-Nikkei
constant dependence
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020


Normal copula
time-varying copula dependence Ethereum-VIX
constant dependence
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020


Normal copula
time-varying copula dependence Monero-VIX
constant dependence
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020


Normal copula
time-varying copula dependence Ripple-VIX
constant dependence
0.1
0.05
0
-0.05
-0.1
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

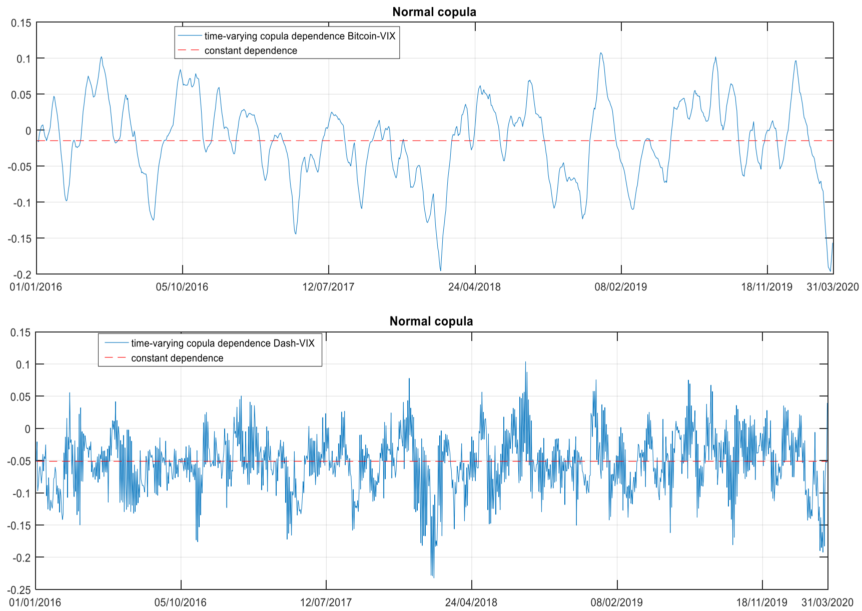


Figure 3. Kendall's Tau Dynamics for Developed Stock Market Indices vs Cryptocurrencies for the Selected Copula
Source: Research finding.

As for the BSE30 index, the dependence is more heterogeneous. Bitcoin and Ripple act as a hedge during the period before December 2019 and a diversifier during the 2020 global pandemic. Ethereum and Bitcoin with the SSE index share the same dependence behavior during the period study and rise during the COVID-19 pandemic. However, for Dash and Ripple, the dependence is altering between positive and negative values. Ethereum act as a hedge between January 2016 to December 2016 and a diversifier during the last period of the study. However, for the case of Dash and Bitcoin the co-movement is altering between positive and negative and, so these currencies act as a safe haven for the RTSI index. The picture of dependence is different for Ripple which rises during the COVID-19 pandemic. Finally, for the BVSP index in relation to the digital assets, Bitcoin act as a diversifier during the whole period of study. However, for Ripple, Dash, and Ethereum the dependence altering between positive and negative values and reaches 0.2 during the pandemic period. These results are consistent with that of Ghorbel and Jeribi (2021a) and Ghorbel and Jeribi (2021b). BRICS indices might have different relationships with most of the cryptocurrencies because the latter are currencies that depend on block-chain technology (Li and Wang, 2017).

Nevertheless, our detailed findings are quite strong and thus require a more in-depth analysis to better understand the factors that drive the heterogeneity. Our findings add to prior studies (e.g., Bouri et al., 2017b; Corbet et al., 2018; Ji et al., 2018; Lahiani et al., 2021; Ghorbel and Jeribi, 2021a; 2021b) by indicating that the hedging and diversifying properties of cryptocurrencies are dissimilar across BRICS indices and by stressing on the fact that not all cryptocurrencies can act as a safe haven or diversifier assets. Our results have implications for investors in BRICS countries. Based on the above findings, investors now can better understand the hedging and diversifying ability of cryptocurrencies.

Table 7. C-vine Dependence Results between Gold, Oil, and Cryptocurrencies

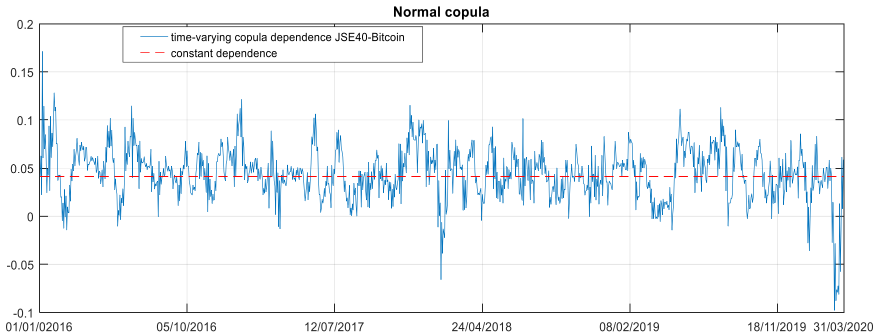
Pair	family	θ	N	LL	W	α	β	LL
Tree 1								
4,1	t	0.43	3.92	132.52	0.05	0.21	1.81	**138.03**
4,5	t	0.54	3.61	202.18	0.19	0.53	1.35	**215.84**
4,6	N	0.05		1.31	0.02	0.007	1.53	**1.32**
4,2	t	0.59	2.24	290.38	0.10	0.45	1.75	**293.86**
4,3	t	0.46	3.73	152.88	0.2	0.21	1.49	136.44
7,4	N	0.06		2.11	0.13	0.11	-0.18	**2.78**
Tree 2								
3,1;4	t	0.50	2.83	286.40	0.18	0.57	1.48	**290.24**
3,5;4	t	0.23	7.59	114.93	0.12	0.32	1.50	**125.24**
3,6;4	N	0.05		2.38	0.11	0.15	0.11	**2.81**
3,2;4	t	0.32	10.00	174.11	0.71	0.41	0.27	161.51
7,3;4	t	-0.02	12.67	3.25	0.02	0.16	0.23	1.97
Tree 3								
2,1;3,4	t	0.08	8.95	122.61	0.39	0.68	0.36	121.97
2,5;3,4	t	0.20	9.96	178.95	0.09	0.15	0.11	**205.96**
2,6;3,4	N	-0.04		0.07	0.005	-0.05	1.69	**0.78**
7,2;3,4	N	0.01		0.91	0.006	0.09	1.72	**4.29**
Tree 4								

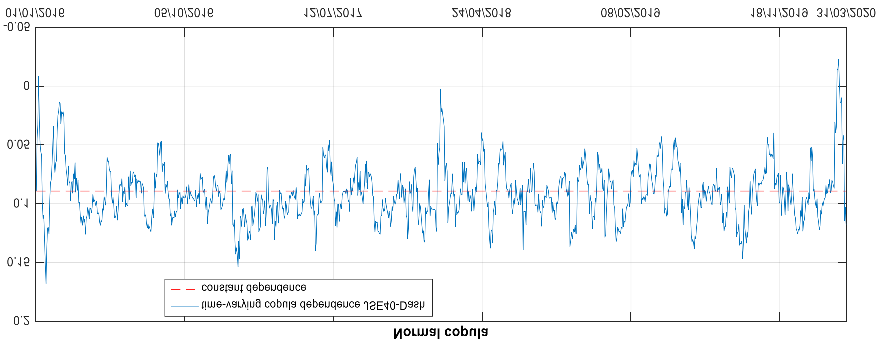
6,1;2,3,4	N	0.05		2.69	0.006	0.03	1.88	**3.83**
6,5;2,3,4	N	0.07		4.38	0.26	-0.20	-0.64	**4.72**
7,6;2,3,4	t	0.03	9.59	5.58	0.10	0.36	-1.32	3.65
Tree 5								
5,1;6,2,3,4	t	0.02	12.34	77.45	0.29	0.55	0.65	**92.23**
7,5;6,2,3,4	N	-0.03		0.02	0.02	-0.57	-1.89	**2.18**
Tree 6								
7,1;5,6,2,3,4	N	-0.01		0.24	0.004	0.08	1.67	**2.27**

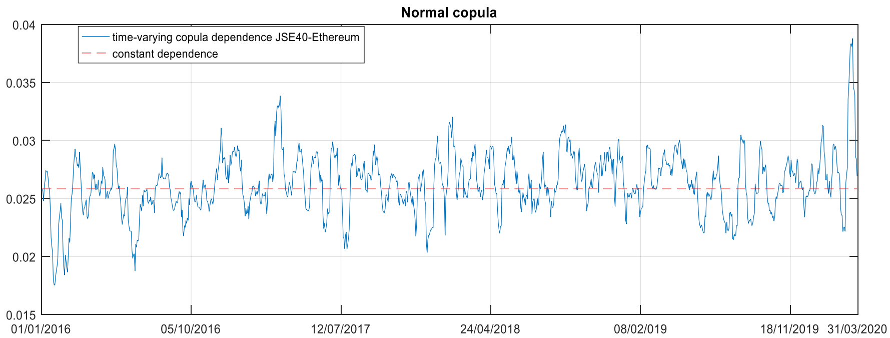
Source: Research finding.
Note: 1 <-> Bitcoin, 2 <-> Dash, 3 <-> Ethereum, 4 <-> Monero, 5 <-> Ripple, 6 <-> Gold, 7 <-> WTI.

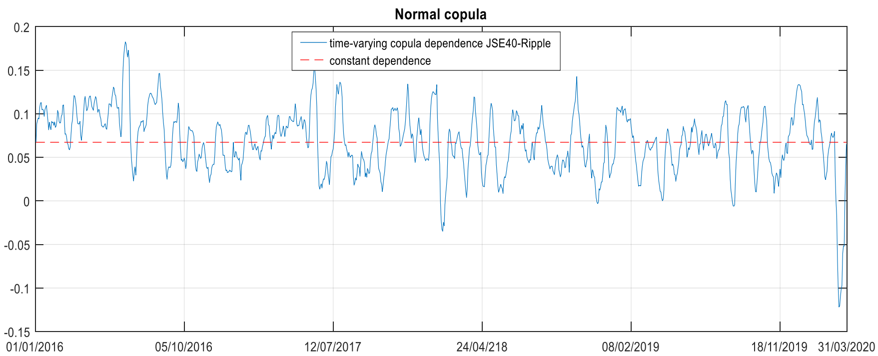
We now switch our analysis to the dependence between digital currencies and commodities. Regarding the two pairs Dash-Gold and Ethereum-Gold, the relationship seems to be more complicated than that of Bitcoin and Ripple with Gold. Ethereum's correlation with Gold is usually positive and increases three times: March 2016, January 2019, and March 2020 during the COVID-19 pandemic. Dash, on the other side, increases its dependence on Gold and altering between positive and negative which moves between -0.07 and 0.15. At the beginning of 2016, this dependence rises and achieves 0.15. However, an opposite behavior is observed at the beginning of March 2020, and the dependence decreases and achieves -0.07.

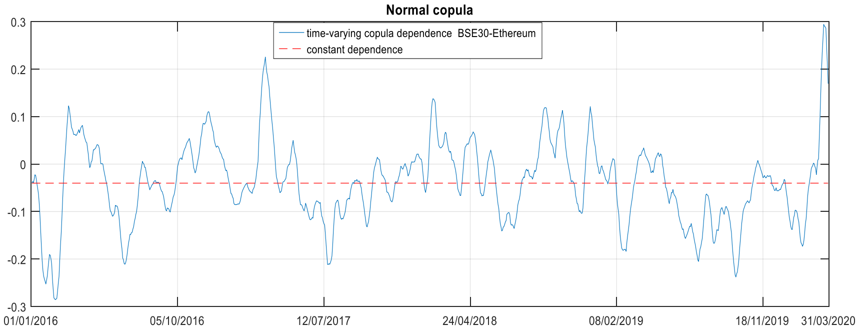
Regarding Ripple's correlation with gold, it decreases starting from February 2020 and achieves -0.02 and increases from March 2020 to achieve 0.16. Moreover, even if we do not see any stable correlation between cryptocurrency and Gold, we, however, observe that the changes in the dependence between Bitcoin and Gold seem to be less volatile compared with the other currencies. The increase of the Bitcoin-Gold dependence in January 2020 happens in parallel with the COVID-19 pandemic. We conclude that Bitcoin and Gold feature no stable dependence. Their dependence is characterized by positive and negative spikes with no general tendency until the end of 2018. Then this relationship becomes positive until the pandemic period. This is consistent with Jareno et al. (2020) who discovered a positive relationship between Bitcoin and Gold.

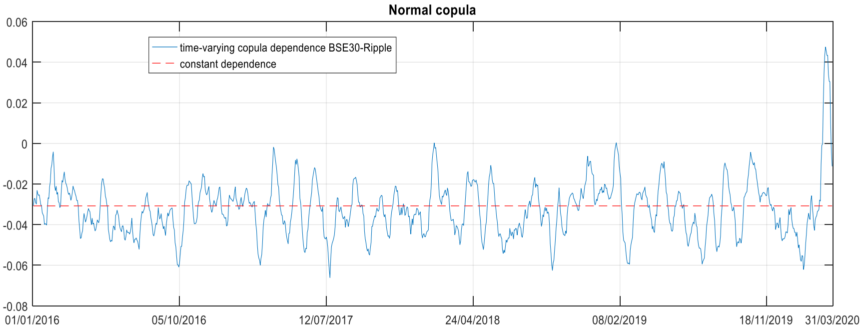

Normal copula
time-varying copula dependence JSE40-Bitcoin
constant dependence
01/01/02016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

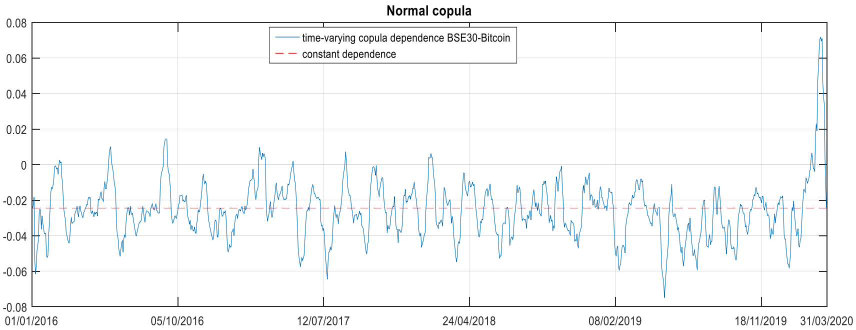

Normal copula
time-varying copula dependence JSE40-Dash
constant dependence
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

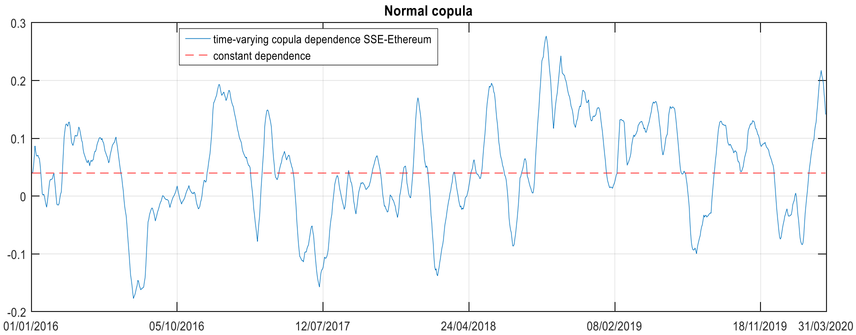

Normal copula
time-varying copula dependence JSE40-Ethereum
constant dependence
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

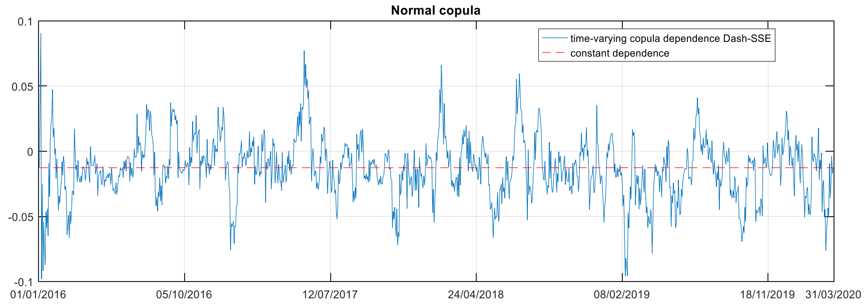

Normal copula
time-varying copula dependence JSE40-Ripple
constant dependence
01/01/2016
05/10/2016
12/07/2017
24/04/218
08/02/2019
18/11/2019
31/03/2020

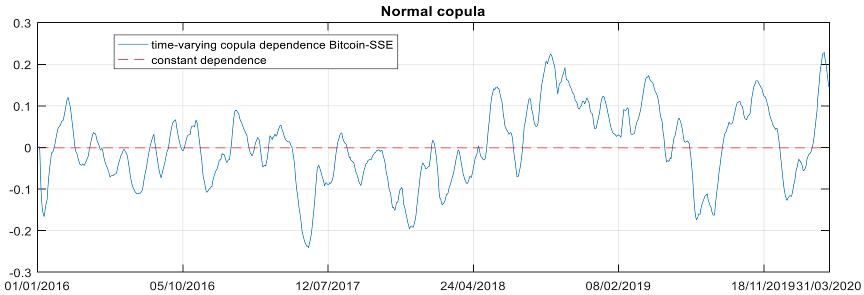

Normal copula
time-varying copula dependence BSE30-Ethereum
constant dependence
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

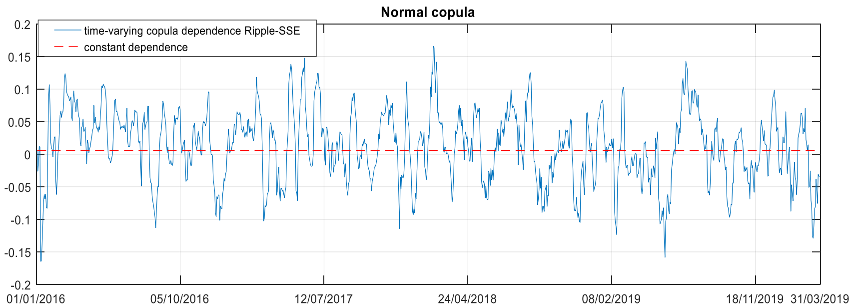

Normal copula
time-varying copula dependence BSE30-Ripple
constant dependence
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

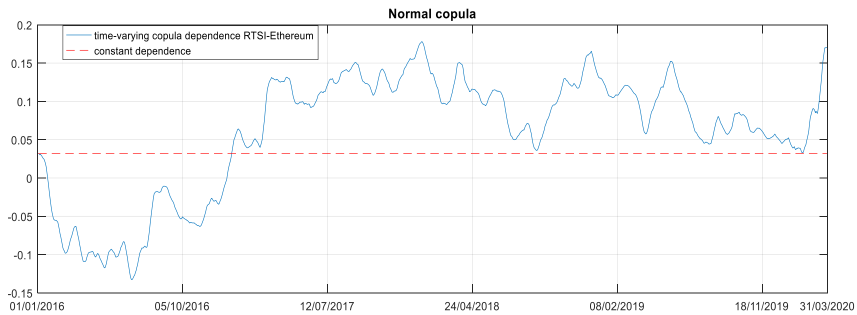

Normal copula
time-varying copula dependence BSE30-Bitcoin
constant dependence
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

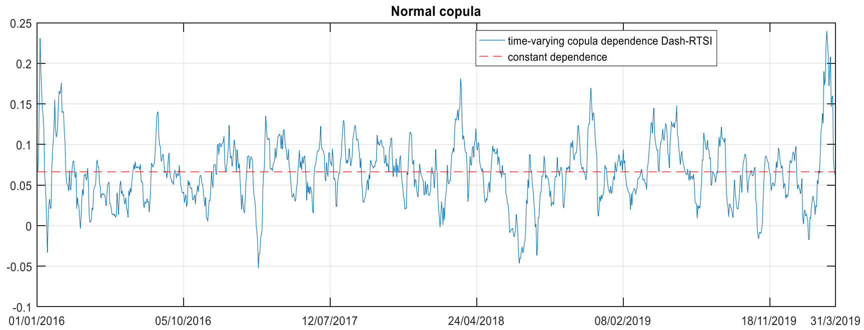

Normal copula
time-varying copula dependence SSE-Ethereum
constant dependence
0.3
0.2
0.1
0
-0.1
-0.2
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

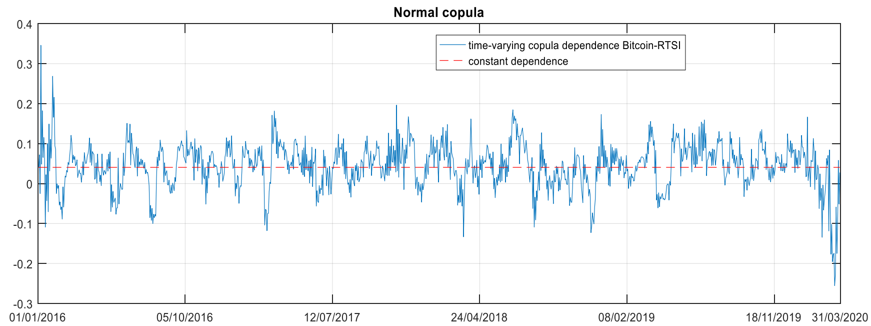

Normal copula
time-varying copula dependence Dash-SSE
constant dependence
0.1
0.05
0
-0.05
-0.1
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

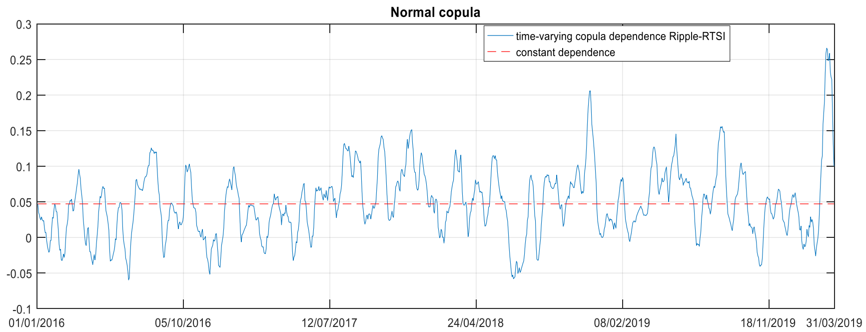

Normal copula
time-varying copula dependence Bitcoin-SSE
constant dependence
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/201931/03/2020

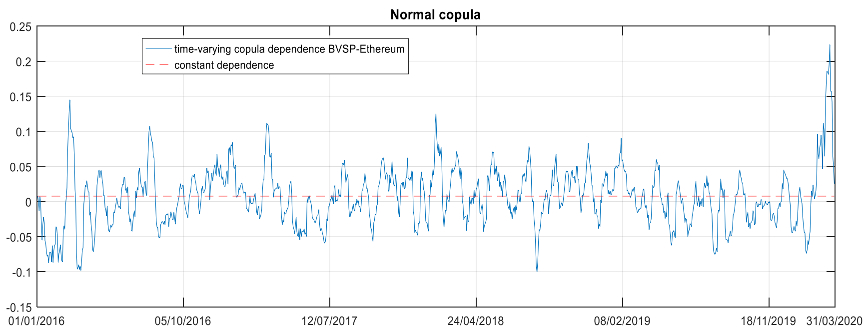

Normal copula
time-varying copula dependence Ripple-SSE
constant dependence
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2019


Normal copula
time-varying copula dependence RTSI-Ethereum
constant dependence
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020


Normal copula
time-varying copula dependence Dash-RTSI
constant dependence
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/3/2019


Normal copula
time-varying copula dependence Bitcoin-RTSI
constant dependence
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020


Normal copula
time-varying copula dependence Ripple-RTSI
constant dependence
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2019


Normal copula
time-varying copula dependence BVSP-Ethereum
constant dependence
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
01/01/2016
05/10/2016
12/07/2017
24/04/2018
08/02/2019
18/11/2019
31/03/2020

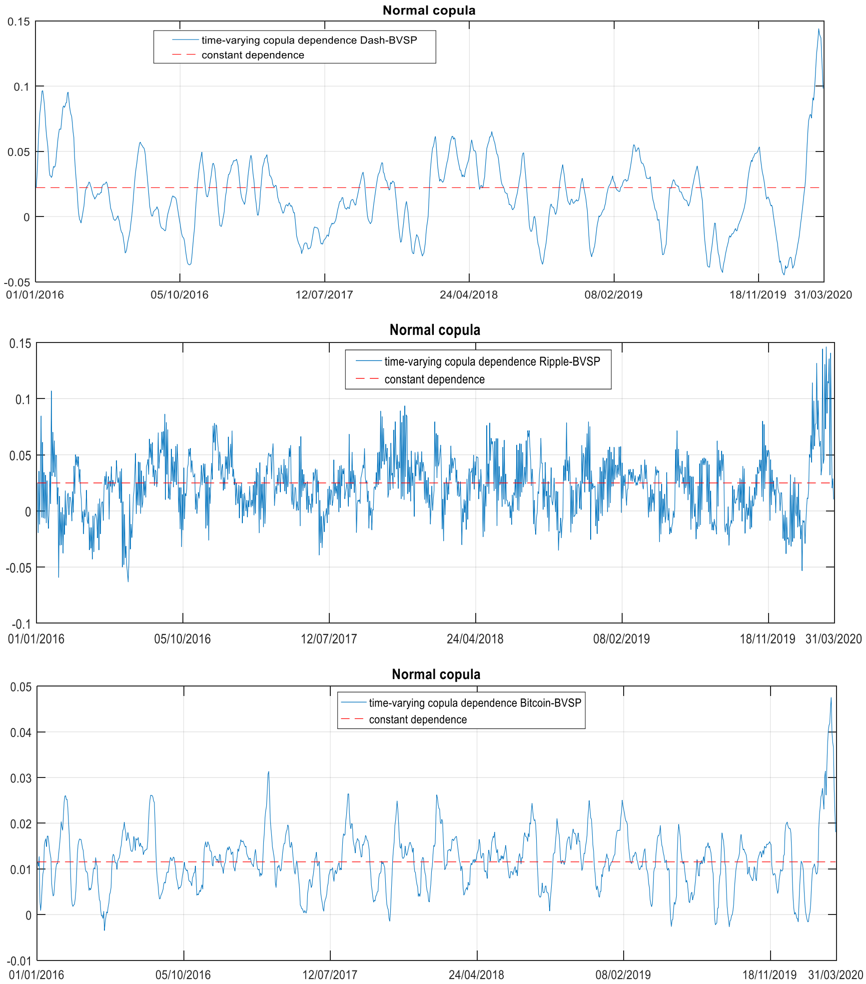
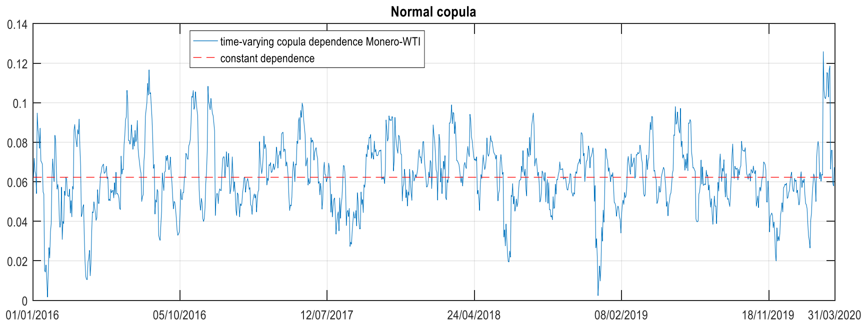
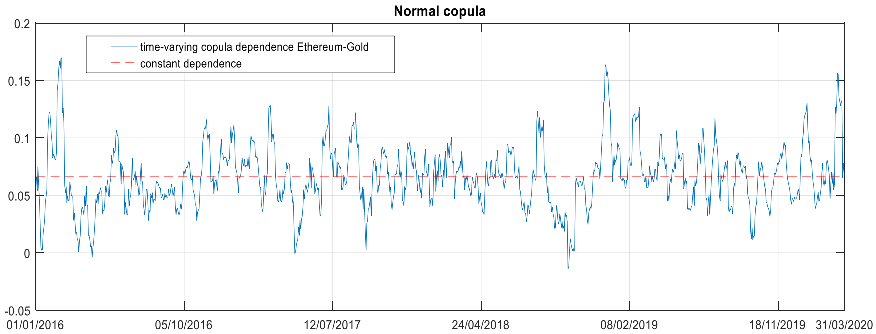
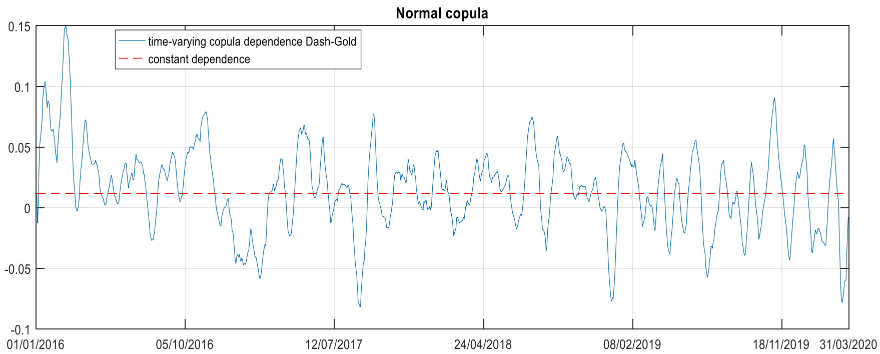


Figure 4. Kendall’s Tau Dynamics for the BRICS Indices vs Cryptocurrencies for the Selected Copula
Source: Research finding.

The dynamic dependence between Monero-Crude Oil is usually positive during the period study and increase during the COVID-19 pandemic to achieve 0.12. In particular, we find that the dynamic dependence between Dash-WTI and Bitcoin-WTI share common features. In fact, the dependence is altering between positive and negative values. For the Dash-Crude Oil dependence, we find that the break date of September 2017 does not correspond to a particular event. March 2020, the break coincides with the COVID-19 pandemic. Regarding the Bitcoin-Crude Oil dependence, we find a single break date, at the end of 2018. During the COVID-19 pandemic, the dependence rises and achieves 0.25. This result is consistent with Ghorbel and Jeribi (2021).







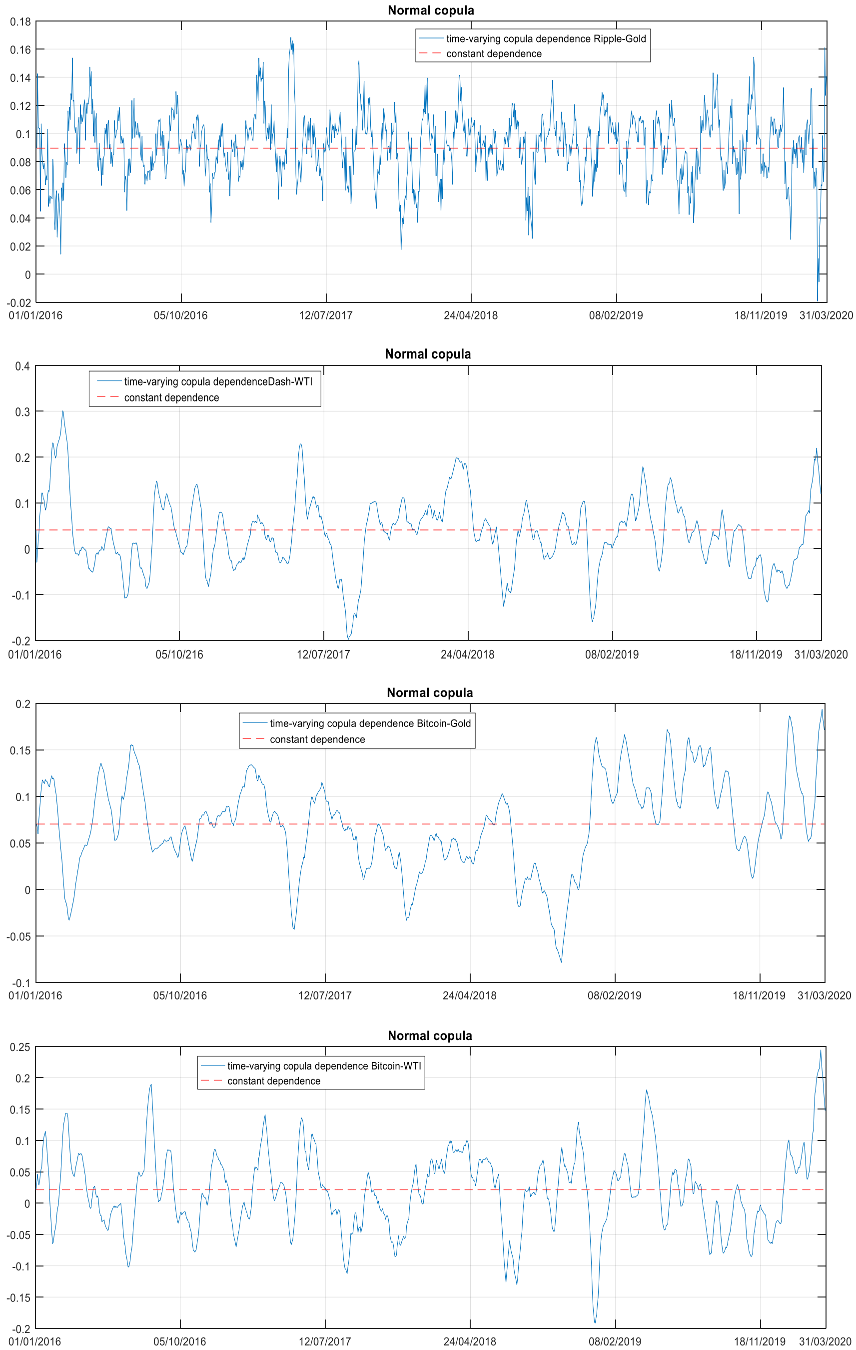


Figure 5. Kendall's Tau Dynamics for vs Cryptocurrencies vs Gold and WTI for the Selected Copula

Source: Research finding.

5. Conclusion

Using the time varying pair copula construction with C – vine copula, the present paper investigates the static and dynamic dependence structure between developed stock market with digital assets, BRICS stock market with digital assets, and finally digital assets with oil and gold. We prove that the use of a dynamic dependence model is useful to investigate the joint behavior of cryptocurrencies, stock market indices, WTI, and Gold. In particular, the structure of the dependence was researched by constructing a complex pattern of the C-vine copula. The dynamic dependence structure of these assets is a key component to grasp the role of these digital assets in the financial and economic landscape.

We found that digital assets are considered as hedge and diversifier assets in all the studied financial markets before the 2020 global pandemic. The dynamic dependence between Bitcoin and stock indices increases in early 2020, except those of Russia and South Africa. Bitcoin can be considered a safe haven asset in these countries. Unlike Ethereum, Dash acts as a safe-haven asset for US, German, Japanese, South African, and Chinese financial investors during the Coronavirus pandemic. In addition, Monero may serve as a good protector against extreme US, German, and Japanese stock markets' co-movements during the COVID-19 outbreak. Ripple can also be used as a safe haven asset in Germany, China, and South Africa. We conclude that the cryptocurrency market is proving to be a more relevant phenomenon for financial markets than previously believed, due to the diversification option it offers investors because of the low level of dependence with the traditional asset class.

Finally, we analyzed the dependence between digital currencies and commodities. Our results indicated that the dynamic dependence between cryptocurrencies and WTI increases in early 2020. Risks among oil markets cannot be hedged by the kind of cryptocurrencies. In addition, the dynamic dependence between cryptocurrencies and Gold follows the same trend except for the couple Gold-Dash. In comparison with commodities, cryptocurrencies have advantage of easy portability thanks to its virtual character, but on the other hand, their virtual character makes them useless or non-existent outside of electronic environment unlikely other tangible commodities.

A direct implication of this finding for investors and market participants is the recommendation to track the progress of the different safe-haven instruments. Thus, portfolio managers may take into account the few eligible cryptocurrencies for inclusion in their portfolios. Speculators in both the stock and cryptocurrency markets may use a spread technique to boost their portfolio return. Moreover, cryptocurrencies serve as a medium of exchange, a unit of account, and a store of value, all of which help to better understand the economy's shock vulnerability. As a result, stock market, cryptocurrency, and commodities behavior are crucial to policymaking and economic activity, especially during a pandemic.

References

Aas, K., Czado, C., Frigessi, A., & Bakken, H. (2009). Pair-Copula Constructions of Multiple Dependence. *Insurance: Mathematics and Economics, 44*(2), 182–198.

Ardia, D., Bluteau, K., & Ruede, M. (2019). Regime changes in Bitcoin GARCH volatility dynamics, *Finance Research Letters*, *29*, 266-271.

Aslanidis, N., Bariviera A. F., & Martínez-Ibañez, O. (2019). An Analysis of Cryptocurrencies Conditional Cross Correlations. *Finance Research Letters, 31*, 130-137.

Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *74*, 3-30.

Baur, D. G., & Lucey, B. M. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *The Financial Review*, *45*(2), 217-229.

Baur, D. G., & McDermott, T. K. (2010). Is Gold a Safe Haven? International Evidence. *Journal of Banking & Finance*, *34*, 1886-1898.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of Exchange or Speculative Assets? *Journal of International Financial Markets, Institutions and Money*, *54*, 177-189.

Beckmann, J., Berger, T., & Czdaj, R. (2015). Does Gold Act As a Hedge or a Safe Haven for Stocks? A Smooth Transition Approach. *Economic Modelling*, *48*, 16-24.

Bedford, T., & Cooke, R. (2002). Vines – A New Graphical Model for Dependent Random Variables. *Annals of Statistics, 30*, 1031-1068.

---------- (2001). Probability Density Decomposition for Conditionally Dependent Random Variables Modeled by Vines. *Annals of Mathematics and Artificial Intelligence*, *32*, 245-268.

Bouri, E., Hagfors, L. I., & Molnar, P. (2017a). On the Hedge and Safe Haven Properties of Bitcoin: Is it really more than a Diversifier? *Finance Research Letters*, *20*, 192-198.

Bouri, E., Jalkh, N., Molnar, P., & Roubaud, D. (2017b). Bitcoin for Energy Commodities before and after the December 2013 Crash: Diversifier, Hedge or Safe Haven? *Applied Economics*, *49*(50), 5063–5073.

Bouri, E., Shahzad, S., Roubaud, D., Kristoufek, L., & Lucey, B. (2020). Bitcoin, Gold, and Commodities as Safe Havens for Stocks: New Insight through Wavelet Analysis. *The Quarterly Review of Economics and Finance, 77*, 156-164.

Bowman, R. G., & Comer, M. R. (2000). The Reaction of World Equity Markets to the Asian Economic Crisis. *University of Auckland, Working Paper, 2000*, 1-51.

Bredin, D., Conlon, T., & Potì, V. (2015). Does Gold Glitter in the Long-Run? Gold as a Hedge and Safe Haven across Time and Investment Horizon. *International Review of Financial Analysis*, *41*, 320-328.

Charfeddine, L., Benlagha, N., & Maouchi, Y. (2020). Investigating the Dynamic Relationship between Cryptocurrencies and Conventional Assets: Implications for Financial Investors. *Economic Modelling*, *85*, 198-217.

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The Economics of Bitcoin Price Formation. *Applied Economics*, *48*(19), 1799-1815.

Conlon, T., & McGee, R. (2020). Safe Haven or Risky Hazard? Bitcoin during the COVID-19 Bear Market. *Finance Research Letters*, *35*, 101-120.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a Financial Asset: A Systematic Analysis. *International Review of Financial Analysis*, *62*, 182-199.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the Dynamic Relationships between Cryptocurrencies and other Financial Assets. *Economics Letters*, *165*, 28-34.

Dyhrberg, A. H. (2016). Hedging Capabilities of Bitcoin. Is it the Virtual Gold? *Finance Research Letters*, *16*, 139-144.

Fakhfekh, M., & Jeribi, A. (2020). Volatility Dynamics of Crypto-Currencies Returns: Evidence from Asymmetric and Long Memory GARCH Models. *Research in International Business and Finance*, *54*, 2-8.

Fakhfekh, M., Jeribi, A., Ghorbel, A., & Hachicha, N. (2021). Hedging stock Market Prices with WTI, Gold, VIX and Cryptocurrencies: a Comparison between DCC, ADCC and GO-GARCH Models. *International Journal of Emerging Markets*, *1746-8809*, 1-29.

Garcia, D., & Schweitzer, F. (2015). Social Signals and Algorithmic Trading of Bitcoin. *Royal Society Open Science*, *2*(9), 1-13.

Garcia-Jorcano, L., & Benito, S. (2020). Studying the Properties of the Bitcoin as a Diversifying and Hedging Asset through a Copula Analysis: Constant and Time-Varying. *Research in International Business and Finance*, *54*,101-113.

Ghorbel, A., & Jeribi, A. (2021a). Investigating the Relationship between Volatilities of Cryptocurrencies and other Financial Assets. *Decisions in Economics and Finance*, *44*, 817-843.

---------- (2021b). Contagion of COVID-19 Pandemic between oil and Financial Assets: the Evidence of Multivariate Markov Switching GARCH Models. *Journal of Investment Compliance, 22*(2), 151-169.

---------- (2021c). Volatility Spillovers and Contagion between Energy Sector and Financial Assets during COVID-19 Crisis Period. *Eurasia Business and Economics Society, 11*, 449-467.

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio Diversification with Virtual Currency: Evidence from Bitcoin. *International Review of Financial Analysis*, *63*, 431-437.

Jareno, F., Gonzalez, M., Tolentino, M., & Sierra, K., (2020). Bitcoin and Gold Price Returns: A Quantile Regression and NARDL Analysis. *Resources Policy*, *67*, 101-116.

Jeribi, A., & Fakhfekh, M. (2021). Portfolio Management and Dependence Structure between Cryptocurrencies and Traditional Assets: Evidence from FIEGARCH-EVT-Copula. *Journal of Asset Management*, *22*(3), 1-16.

Jeribi, A., & Ghorbel, A. (2021). Forecasting Developed and BRICS Stock Markets with Cryptocurrencies and Gold: Generalized Orthogonal Generalized Autoregressive Conditional Heteroskedasticity and Generalized Autoregressive Score Analysis. *International Journal of Emerging Markets, 1746-8809*, 1-31.

Jeribi, A., & Masmoudi, K. W. (2021). Investigating Dynamic Interdependencies between Traditional and Digital Assets during the COVID-19 Outbreak: Implications for G7 and Chinese Financial Investors. *Journal of Research in Emerging Markets*, *3*(3), 60-80.

Jeribi, A., & Snene Manzli, Y. (2021). Can Cryptocurrencies be a Safe Haven during the Novel COVID-19 Pandemic? Evidence from the Tunisian Stock Market. *Journal of Research in Emerging Markets*, *3*(1), 14-31.

Jeribi, A., Chamsa, D., & Snene_Manzli, Y. (2020). Emerging Stock Markets' Reaction to COVID-19: Can Cryptocurrencies be a Safe Haven? *Journal of Management and Economic Studies*, *2*(3), 152-165.

Jeribi, A., Jena, S. K., & Lahiani, A. (2021). Are Cryptocurrencies a Backstop for the Stock Market in a COVID-19-Led Financial Crisis? Evidence from the NARDL Approach. *International Journal of Financial Studies, 9*(3), 33-45.

Joe, H. (1997). *Multivariate Models and Dependence Concepts*. London: Chapman & Hall.

Kajtazi, A., & Moro, A. (2019). The Role of Bitcoin in Well Diversified Portfolios: A Comparative Global Study. *International Review of Financial Analysis*, *61*, 143-157.

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold-A Comparison of Volatility, Correlation, and Portfolio Performance. *International Review of Financial Analysis, 59*, 105-116.

Lahiani, A, Jeribi, A., & Jlassi, N. (2021). Nonlinear Tail Dependence in Cryptocurrency-Stock Market Returns: The Role of Bitcoin Futures. *Research in International Business and Finance*, *56*, 101-135.

Lehkonen, H., & Heimonen, K. (2014). Timescale-Dependent Stock Market Co-Movement: BRICs vs. Developed Markets. *Journal of Empirical Finance*, *28*, 90-103.

Lucey, M., & Li, S. (2014). What Precious Metals Act as Safe Havens, and When? Some US Evidence. *Applied Economics Letters*, *22*, 35-45.

Malevergne, Y., & Sornette, D. (2003). Testing the Gaussian Copula Hypothesis for Financial Assets Dependences. *Finance, 3*, 231-250.

Mensi, W., Hkiri, B., Al-Yahyaee, K. H., & Kang, S. H. (2018). Analyzing time–Frequency Co-Movements across Gold and Oil Prices with BRICS Stock Markets: A VaR Based on Wavelet Approach. *International Review of Economics & Finance, 54*, 74-102.

Mensi, W., Shahzad, S. J. H., Hammoudeh, S., Zeitun, R., & Rehman, M. U. (2017). Diversification Potential of Asian Frontier, BRIC Emerging and Major Developed Stock Markets: A Wavelet-Based Value at Risk Approach. *Emerging Markets Review*, *32*, 130-147.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. Retrieved from http://bitcoin.org/bitcoin.pdf

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, *59*, 347-370.

---------- (1990). ARCH Models as Diffusion Approximations. *Journal of Econometrics*, *45*, 7-38.

Pasutasarayut, P., & Chintrakarn, P. (2012). Is Gold a Hedge or Safe Haven? A Case Study of Thailand. *European Journal of Scientific Research*, *74*, 90-95.

Platanakis, E., & Urquhart, A. (2020). Should Investors Include Bitcoin in their Portfolios? A Portfolio Theory Approach. *The British Accounting Review*, *52*(4), 100-118.

Salisu, A. A., Ebuh, G. U., & Usman, N. (2020). Revisiting Oil-Stock Nexus during COVID-19 Pandemic: Some Preliminary Results. *The International Review of Economics & Finance*, *69*, 280-294.

Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018). *Is Bitcoin a Hedge, a Safe Haven or a Diversifier for Oil Price Movements? A Comparison with Gold*. *Energy Economics*, *74*, 787-801.

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L. (2020). Safe Haven, Hedge and Diversification for G7 Stock Markets: Gold versus Bitcoin. *Economic Modelling*, *87*, 212-224.

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better Safe-Haven Investment than Gold and Commodities? *International Review of Financial Analysis*, *63*, 322-330.

Sharif, A., Aloui, C., & Yarovaya, L. (2020). Covid-19 Pandemic, Oil Prices, Stock Market, Geopolitical Risk and Policy Uncertainty Nexus in the US Economy: Fresh Evidence from the Wavelet-based Approach. *International Review of Financial Analysis*, *70*, 101-114.

Syriopoulos, T., Beljid, M., & Boubaker, A. (2015). Stock Market Volatility Spillovers and Portfolio Hedging: BRICS and the Financial Crisis. *International Review of Financial Analysis*, *39*, 7-18.

Tiwari, A. K., Raheem, I. D., & Kang, S. H. (2019). Time-varying Dynamic Conditional Correlation between Stock and Cryptocurrency Markets Using the Copula-ADCC-EGARCH Model. *Physica A*, *535*, 1-9.