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ORIGINAL ARTICLE

Portfolio management and dependence structure between cryptocurrencies and traditional assets: evidence from FIEGARCH-EVT-Copula

Ahmed Jeribi[1] · Mohamed Fakhfekh[2]

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Abstract
The purpose of this paper is twofold. Firstly, it discusses the relationship between five cryptocurrencies, oil prices, and US indices. Secondly, it focuses on determining the best portfolio hedging strategy. Using daily data relevant to the period ranging from January 4, 2016, to November 29, 2019, this study applies the FIEGARCH-EVT-Copula and Hedge ratios analysis. The findings obtained have shown that the crude oil (WTI) and the US indices return highlights the persistence of a negative and significant leverage effect while the cryptocurrency markets present a positive asymmetric volatility effect. Moreover, this paper show evidence of very weak dependence between all the different pairs considered before and after the introduction of Bitcoin Futures. Based on the Hedging ratio and mean-variance approach, this article suggests that to minimize the risk while keeping the same expected returns of the digital-conventional financial asset portfolio, the investor should hold more conventional financial assets than digital assets except for WTI-Bitcoin, WTI- Dash and WTI-Ethereum pairs which the values of their hedge ratios are rather important with respect to OLS regression.

Keywords Extreme dependence structure · Copula approach · Hedge ratio · Cryptocurrencies · Traditional assets · Bitcoin futures

Introduction

Cryptocurrency is a relatively new phenomenon that becomes popular since the introduction of the Bitcoin concept by Nakamoto 2008. In fact, a growing number of studies has investigated the volatility of cryptocurrencies (Bouoiyour and Selmi 2015, 2016; Bouri et al. 2017; Fakhfekh and Jeribi 2020), the correlation between cryptocurrencies and other traditional assets (Klein et al. 2018; Aslanidis et al. 2019; Katsiampa et al. 2019), the portfolio diversification with cryptocurrencies (Brière et al. 2015; Bouri et al. 2017; Dorfleitner and Lung 2018; Guesmi et al. 2019; Kajtazi and Moro 2019; Symitsi and Chalvatzis 2019; Charfeddine et al. 2020).

Following the recent substantial increase in attention to the cryptocurrencies market and the meteoric increase in Bitcoin price 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), several studies have sought to uncover the effect of this introduction on the Bitcoin market. Hale et al. (2018) suggested that the introduction of Bitcoin futures contributed to a rapid decline in Bitcoin's price immediately after its appearance by allowing pessimistic investors to enter the market which has contributed to a rapid decline in Bitcoin's value. Ruozhou et al. (2019) also argued that the launch of Bitcoin futures was in a certain time responsible for the crash of Bitcoin. These authors found a significant and negative relationship between the introduction of Bitcoin futures and Bitcoin return. However, concerning other cryptocurrencies, the relationship is either positive or insignificant.

Corbet et al. (2018a) investigated the ability of the introduction of futures trading in Bitcoin to resolve the issues that stopped Bitcoin to be considered as a currency.

Ahmed Jeribi
ahmedjeribi07@yahoo.fr

Mohamed Fakhfekh
fakhfekh_moh@yahoo.fr

[1] Faculty of Economics and Management of Mahdia, Mahdia, Tunisia

[2] Higher Institute of Business Administration of Sfax, Sfax, Tunisia

Their analysis shows that volatility increased following the appearance of futures contracts. The analysis conducted also proves that future contracts are not considered as hedging instruments, that price discovery is driven by uninformed noise traders in the spot market and that Bitcoin is a speculative asset rather than a currency as it is shown in Yermack (2015). The effects of the introduction of Bitcoin futures on the volatility of Bitcoin returns have been also studied by Kim et al. (2019) who have examined the change in realized volatility. These authors found that immediately after the introduction of Bitcoin futures, the Bitcoin market became more volatile and more stable than it was before. Yaya et al. (2019) examined Bitcoin's persistence and inter-dependence with other cryptocurrencies before and after the Bitcoin crash. Their results show a higher persistence of price shocks after the crash. In addition, the cointegration relationships between Bitcoin and other cryptocurrencies exist before and after the Bitcoin crash, with weak correlations observed in the post-crash period.

Modeling the volatility dynamics between cryptocurrencies and other assets is an important and new topic to study, because recent developments in increased integration between financial markets and the emergence of cryptocurrencies markets offer investors new methods of diversification, hedging and risk management of their investment portfolios. Gajardo et al. (2018) used the MF-ADCCA to analyze the asymmetry of the cross-correlations between the major currency rates and Bitcoin, Bitcoin and WTI, GOLD and DJIA. They found that there is multifractality in every cross-correlation studied. They also found that asymmetry exists in the cross-correlation exponents under the different trends of Gold, DJIA, and WTI. Their results proved that Bitcoin represents greater multi-fractal spectra than the other currencies on its cross-correlation with the WTI, the Gold and the DJIA. There is also a clear different relationship between Bitcoin and other commodities on the one hand and Bitcoin and stock market indices on the other hand. Using the BEKK-GARCH model, Klein et al. (2018) investigate the time-varying conditional correlations of cryptocurrencies in comparison to commodities and stock indices. Their study shows that gold plays an important role in financial markets with flight-to-quality in times of market distress. However, Bitcoin acts like the exact opposite and it is positively correlated with downward markets. They also analyzed the properties of Bitcoin as a portfolio component and found no evidence for stable hedging capabilities. They concluded that Bitcoin and Gold have different properties as assets. Symitsi and Chalvatzis (2019) assessed the performance of benchmark portfolios of currencies, gold, oil, and stocks. They also analyzed the performance of a multi-asset portfolio of these various asset classes with respective portfolios that invest additionally in Bitcoin under four trading strategies. They found significant diversification benefits from the inclusion of Bitcoin.

Most of the works analyze returns and treat volatility for Bitcoin as the cryptocurrency market's leader. A number of new cryptocurrencies appear and most of them are developed further on the basis of blockchains. However, most of the literature focuses on Bitcoin only. Corbet et al. (2018b) analyzed the relationships between three cryptocurrencies (Bitcoin, Ripple, and Litecoin) and a variety of other financial assets. Their results as those of Corbet et al. (2019) found that cryptocurrencies are rather isolated from the other markets. In fact, the values for directional return and volatility from Bond, Gold, VIX, FX, GSCI and S&P 500 to cryptocurrency markets are very low. Thereby, they suggest a role for cryptocurrencies as diversifier assets for investors with short investment horizons. Using a generalized DCC class model, Aslanidis et al. (2019) explored the behavior of conditional correlations among four cryptocurrencies (Bitcoin, Monero, Dash, and Ripple), S&P 500, Bond and Gold. They suggest that the studied cryptocurrencies are positively correlated and the correlations between cryptocurrencies and traditional financial assets are negligible.

Charfeddine et al. (2020) investigated the economic and financial benefits of Bitcoin and Ethereum, for financial investors by studying their capabilities to generate benefits from portfolio diversification and hedging strategies. By estimating static and time-varying tail copulas, they found evidence of time-varying dependence and the absence of any asymmetric tail dependence between digital and conventional financial assets. They suggested that digital assets can offer new opportunities for portfolio diversification by including only a small weight of cryptocurrencies to a portfolio of traditional financial assets. Tiwari et al. (2020) examined the time-varying correlations between S&P 500 and six cryptocurrencies using a copula-ADCC-EGARCH model. They identified a very low overall time-varying correlation, indicating that cryptocurrencies are considered as a hedge against the risk of S&P 500.

Traditionally, the interdependence between stock markets is measured using the Pearson coefficient, which works from the assumption that the relationships between financial assets are linear and that financial assets are normally distributed. However, recent studies have demonstrated that the correlations between asset returns are both nonlinear and time-varying. Specifically, most return distributions show asymmetric upside and downside movements, as well as fat tails. In this case, it has become a significant challenge in risk management to use a more appropriate approach to model dependencies between asset returns. Combining copula functions with GARCH models and extreme value theory takes into account not only the occurrence of extreme and rare events and the volatility clustering phenomenon. It takes better also account the dependency structure between markets during quiet periods as well as during periods of strong disturbances than other methods and techniques likes the BEKK model, DCC-MGARCH model, VAR models (Ghorbel and Trabelsi 2014). These combinations improve risk modeling and ameliorate the effectiveness of portfolio management.

In this context, this paper differs from previous studies in many aspects. First, 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 digital assets and includes Dash, Monero and Ripple in the analysis. Second, using the most up-to-date dataset, the period covered in this paper is from January 2016 to November 2019. In order to cover the effect of the introduction of Bitcoin futures by the Chicago mercantile exchange (CME) and the Chicago Board Options Exchange (CBOE), the research period is divided into two sub-periods. Third, the value added by this study to the literature by appealing the AR (1)-FIEGARCH-EVT-copula model is as follow: firstly, it analyses the volatility dynamics, long memory properties and asymmetric effects of five popular cryptocurrencies and traditional financial assets such as S&P 500, NASDAQ and WTI before and after the launch of Bitcoin futures; secondly, it estimates the extreme dependence structure between cryptocurrencies and traditional financial assets. Ultimately, an eventual determination of the optimal hedging strategy under the FIEGARCH-EVT-copula and OLS regressions, likely to help minimize the overall risk portfolio is identified.

This paper is organized as follows. Section 2 presents the econometric methodology. Section 3 presents and discusses both the data and the estimation results. Finally, the conclusion and research perspectives are depicted in Sect. 4.

Econometric methodology

To eliminate the problem of autocorrelation, stylized facts (non-normality of the distribution, nonlinearity of the structure dependence between financial series) and shock asymmetry among the financial series, we apply a Fractionally Integrated Exponential GARCH (FIEGARCH) model (p, d, q) to cater for both of the shock asymmetry and persistence issues. Indeed, this particular model selection takes into account both ARCH as well as long memory effects. Developed by Bollerslev and Mikkelsen (1996), the model can be written as follows:

$$\begin{aligned} &\ln(h_t) = \omega + \phi(L)^{-1}(1-L)^{-d}[1+\alpha(L)]g\left(z_{t-1}\right) \\ &\text{with}: g\left(z_t\right) = \gamma_1 z_t + \gamma_2\left[\left|z_t\right| - E\left|z_t\right|\right] \end{aligned} \tag{1}$$

Just like the FIGARCH (p, d, q) specification, the FIEGARCH (p, d, q) model is reduced to the EGARCH one in case $d = 0$, and to the integrated EGARCH (IEGARCH) model in case $d = 1$. By analogy to the ARFIMA class of models, $\left\{\ln(h_t)\right\}$ is in stationary covariance and invertible for d within the interval [− 0.5, 0.5] (Bollerslev and Mikkelsen 1996). Besides, the long-memory properties would dissipate for the entire values of $d < 1$. We suppose that the return equation is written as follow:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \tag{2}$$

With r_t denoting return index at time t, r_{t-1} is the return index at time $t-1$ and α_0, α_1 are parameters.

The present work tries to examine the dependence structure between cryptocurrencies and stock market indices, so as to draw conclusions from the results of the optimal Hedge ratios. Indeed, a four-step approach will be adopted in this respect. Firstly, residues need to be filtered through an AR (1)-FIEGARCH (1, d 1) model. Secondly, the Extreme Values Theory (EVT) is used to extract extreme values and rare events, such as oil shocks and financial crises, can be identified as they may have adverse effects on the financial time series' volatility. At this level, this study adopted the "High Over Thresholds (POT)" method. As outliers, 30% of the observations are selected (15% pertain to the large-value observations, and 15% are of smaller values), before estimating the GEV distribution parameters of extreme values, as obtained through the POT method. Thirdly, the dependence structures among extreme series are estimated through copula theory.

Actually, analysis of the relationship between both markets requires knowledge of the underlying dependence structure persisting among them. Hence, a flexible copula would provide a representation of the dependency structure connecting the margins for a distribution function with several variables. In this respect, the Sklar's (1959) theorem states that the joint distributions of two continuous random variables X and Y, $F_{XY}(x, y)$, with marginal functions $F_X(x)$ and $F_Y(y)$, is described by a copula function C such that:

$$F_{XY}(x, y) = C\left(\mathrm{F_X(x)},\ \mathrm{F_Y(y)}\right) \tag{3}$$

In financial and economic literature, modeling multivariate distributions constitute a crucial issue. To avoid a high complexity level, the bivariate distribution copula method will be used to model the dependence relationship underlying two variables. In general, there exist three major bivariate-copula families, namely elliptical (Normal and Normal mixture), Archimedean (Clayton and Frank) and EVT copulas (Gumbel, Tawn). Indeed, while the symmetric dependency on both tails is examined by the elliptical family, the left tail can be captured by the Clayton copula and the right tail by the Gumbel copula. With respect to our study case, Normal and Normal mixture copulas and seven Archimedean copulas (Frank, Clayton,

Table 1 Distribution and characteristic of diverse copula models

Nature	Copula	Distribution	Parameter
Elliptical copula	Normal	$C(u_1,u_2) = \int_{-\infty}^{\phi^{-1}(u_1)} \mathrm{d}x \int_{-\infty}^{\phi^{-1}(u_2)} \mathrm{d}y \frac{1}{2\pi\sqrt{1-\delta^2}} e^{\left(-\frac{x^2-2\delta xy+y^2}{2(1-\delta^2)}\right)}$	$0 \le \delta \le 1$
	Normal mix	$C(u_1,u_2) = pC_{\delta_1}(u_1,u_2) + (1-p)C_{\delta_2}(u_1,u_2)$	$p \ge 0;\ \delta_1,\delta_2 \le 1$
EV Copulas	Gumbel	$C(u_1,u_2;a) = \mathrm{e}^{\left(-[(-\ln u_1)^a+(-\ln u_2)^a]^{\frac{1}{a}}\right)}$	a∈[1,∞)
	Galambos	$C(u_1,u_2) = u_1 u_2 e^{\left[-Ln(u_1)^{-\delta}-Ln(u_2)^{-\delta}\right]^{-\frac{1}{\delta}}}$	$0 \le \delta < \infty$
	Husler and Reiss	$C(u_1,u_2) = e^{\left(Ln(u_1)\phi\left[\frac{1}{\delta}+\frac{1}{2}\delta Ln\left(\frac{Ln(u_1)}{Ln(u_2)}\right)\right]+Ln(u_2)\phi\left[\frac{1}{\delta}+\frac{1}{2}\delta Ln\left(\frac{Ln(u_2)}{Ln(u_1)}\right)\right]\right)}$	$0 \le \delta < \infty$
	Tawn	$A(t) = 1-\beta+(\beta-\alpha)t+\left[\alpha^r t^r+\beta^r(1-t)^r\right]^{1/r}$	$0 \le \alpha,\beta \le 1, 1 \le r < \infty$
	BB5	$C(u_1,u_2) = 1-\left((1-u_1)^\alpha+(1-u_2)^\alpha-(1-u_1)^\alpha(1-u_2)^\alpha\right)^{1/\alpha}$	α ≥ 1
Archimedean copulas	Frank	$C(u_1,u_2) = -\frac{1}{a}\ln(1+\frac{(e^{-au_1}-1)(e^{-au_2}-1)}{(e^{-a}-1)}$	0 <α<∞
	Clayton	$C(u_1,u_2) = \left(u_1^{-\alpha}+u_2^{-\alpha}-1\right)^{-1/\alpha}$	α∈[−1,∞)\{0}
	BB1	$C(u_1,u_2) = \left(1+\left[(u_1^{-\theta}-1)^\delta+(u_2^{-\theta}-1)^\delta\right]^{-\frac{1}{\theta}}\right)$	$\theta > 0;\ \delta \ge 1$
	BB2	$C(u_1,u_2) = \left(1+\delta^{-1}Ln\left[e^{\delta u_1^{-\theta}}+e^{\delta u_2^{-\theta}}-1\right]\right)^{\frac{1}{\theta}}$	$\theta > 0;\ \delta > 0$
	BB3	$C(u_1,u_2) = e^{\left(-\left[\delta^{-1}Ln\left[e^{\delta(-Ln(u_1))^{-\theta}}+e^{e^{\delta(-Ln(u_2))^{-\theta}}}-1\right]\right]^{\frac{1}{\theta}}\right)}$	$\theta > 1;\ \delta > 0$
	BB6	$C(u_1,u_2) = 1-\left(1-e^{-\left\{\left(-Ln\left(1-(1-u_1)^\theta\right)\right)^\delta+\left(-Ln\left(1-(1-u_2)^\theta\right)\right)^\delta\right\}^{\frac{1}{\delta}}}\right)^{\frac{1}{\theta}}$	$\theta \ge 1;\ \delta \ge 1$
	BB7	$C(u_1,u_2;\theta,\delta) = 1-(1-\left[(1-(1-u_1)^\theta)^{-\delta}+(1-(1-u_2)^\theta)^{-\delta}-1\right]^{-\frac{1}{\delta}^{1/\theta}}$	θ ≥ 1 and δ > 0
Archimax copulas	BB4	$C(u_1,u_2;\theta,\delta) = \left(u_1^{-\theta}+u_2^{-\theta}-1-\left[(u_1^{-\theta}-1)^{-\delta}+(u_2^{-\theta}-1)^{-\delta}\right]^{-\frac{1}{\delta}}\right)^{-1/\theta}$	θ ≥ 0 and δ > 0

BB1, BB2, BB3, BB6, and BB7) are applied, along with five EVT copulas (Gumbel, Galambos, Husler Reiss, BB5 and Tawn) and the Archimax copula (BB4). As depicted in Table 1, the entirety of these copulas helps provide the relevant functional form as well as dependence parameters.

At this stage, it consists in estimating the dependence coefficient, as used to calculate the Hedging ratio necessary for proving how the US indices and oil price-related risk can be effectively hedged. For a more thorough illustration of the scenario, let's consider an investor wanting to hedge his portfolio position against US indices and oil price fluctuation. In such a case, the investor faces the problem of minimizing his portfolio related risk without reducing its expected return. According to Kroner and Sultan (1993), in regard to an investor desiring to determine the optimal hedge ratio for his proper portfolio, the hedge ratio is calculated as follow:

$$\beta_t^{SO} = \frac{h_t^{SO}}{h_t^S} \tag{4}$$

In order to minimize the risk, the hedging strategy as considered involves finding how much a long position (buy) of one dollar in the US indices and oil market should be hedged by a short position (sell) of β dollar in the stock market index.

where:

- β_t denotes the risk-minimizing hedge ratio for market indices and oil market.
- h_t^s represents the conditional variances of the stock market index.
- h_t^{so} refers to the conditional covariance between oil and stock market returns at time t.

The performance of different optimal hedge ratios obtained from different cryptocurrencies is measured using the hedging effectiveness (HE) index (Chang et al. 2011; Ku et al. 2007).

$$HE = \frac{var_{\text{unhedged}} - var_{\text{hedged}}}{var_{\text{unhedged}}} \quad (5)$$

A higher *HE* index indicates a higher hedging effectiveness

Data and results

The empirical study research involves 1007 daily observations of five cryptocurrencies (Bitcoin, Dash, Monero, Ripple and Ethereum) as well as WTI, S&P 500 and Nasdaq stock market indices, sampled from January 4, 2016, to November 29, 2019. In order to cover the effect of the introduction of Bitcoin futures by the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE)[1], the research period is divided into two sub-periods. The first sub-period is called the period before the introduction, goes from January 04, 2016, to December 18, 2017. The second one is the period after the introduction of Bitcoin futures and it goes from December 19, 2017, to November 19, 2019.

The database was collected from the Data Stream, Coin Market Cap and ABC bourse basis. Daily returns are defined by $r_t = ln\left(p_t/p_{t-1}\right)$, with $P_{i,t}$ denoting indices I closing price at time t. In the literature, this transformation of data is usually employed for index series to obtain stationary data. In addition, Fig. 1 confirms that the return series are stationary.

The entirety of the series' pertaining descriptive statistics for the different period is depicted in the following table (Figs. 2 and 3):

Table 2 reports the five cryptocurrencies, the WTI oil price and S&P 500 as well as NASDAQ indices descriptive statistics during the three periods: the period after the introduction of futures (Period 1), the period before the introduction (Period 2) and the whole period (Period 3). Worth highlighting, mean returns have proven to be very small in respect of standard deviations. The entirety of Skewness statistics during the three periods showed that the marginal distributions are asymmetrical to the right in which the values are positive, or to the left, where they appear to be negative. The Kurtosis statistics high values seem to be consistent with fat tails in return distributions.

As a matter of fact, the normality hypothesis turns out to be rejected with regard to all series, given the Jarque–Bera test high value. Moreover, the Ljung–Box statistic Q(16) and $Q^2(16)$ suggests well the persistence of a serial correlation in the entirety of the series' return volatility during the three periods except some series of returns, with the ARCH effects being prevalent in all returns series, due to the significantly high value of the autoregressive conditional heteroskedasticity–Lagrange multiplier (ARCH–LM) statistic. Still, the modified R/S test sounds to reveal the predominance of long memory within the entirety of the volatility return series. This result is similar to that of Fakhfekh and Jeribi (2020), but inconsistent with Charfeddine et al. (2020).

FIEGARCH model

The long-memory persistence, noticed in the return series, allows for using such nonlinear long-memory models as the Fractional Integrated Exponential GARCH model. Consequently, the shock-asymmetry effect on volatility could be integrated within this model in a bid to account for the return series' financial leverage effect. Thus, we choose the AR (1)-FIEGARCH (1, d, 1) model to explain the cryptocurrencies, the stock indexes, and oil price volatility. The estimation results of the model, as defined in both equations1 and 2, are shown in the following table.

As can be noticed, the FIEGARCH model appears, in turn, to capture both of the asymmetric-shock and financial-leverage effect. As indicated in Table 3, the leverage-effect coefficient LEV(1) seems to be statistically significant with respect to all indexes during the three periods except for the Bitcoin and the Monero during the period after the introduction of futures. Thus, the results highlight the persistence of a negative and significant leverage effect concerning the WTI, NASDAQ and S&P 500 returns during the three periods. The negative coefficient implies that negative shocks increase the volatility by less than positive shocks which are in stark contrast to the positive coefficient generally reported in stock markets (Jeribi et al. 2015; Fakhfekh et al. 2016). These results are confirmed by Kristoufek (2014), Choi and Shin (2018).

The trading of uninformed investors leads to a rise in the volatility while informed investors' trading reduces it. Avramov et al. (2006) argue that price changes due to uninformed investors will be reversed increasing volatility by more than price changes due to informed investors. The inverted asymmetric effect (for all cryptocurrencies) can be explained with the herding of uninformed investors if prices go up and contrarian behavior of informed investors if prices go down. The AR(1) coefficients also indicate that uninformed investors play a significant role for all crypto-currencies since the coefficient AR (1) is almost the same for all crypto-currencies. This result is in line with

[1] Although CBOE opened a futures market on December 10, trading volume was too small until the CME launched Bitcoin futures (Hale et al. 2018) on December 18, 2017, so we choose December 18, 2017, as the day when Bitcoin futures were introduced.

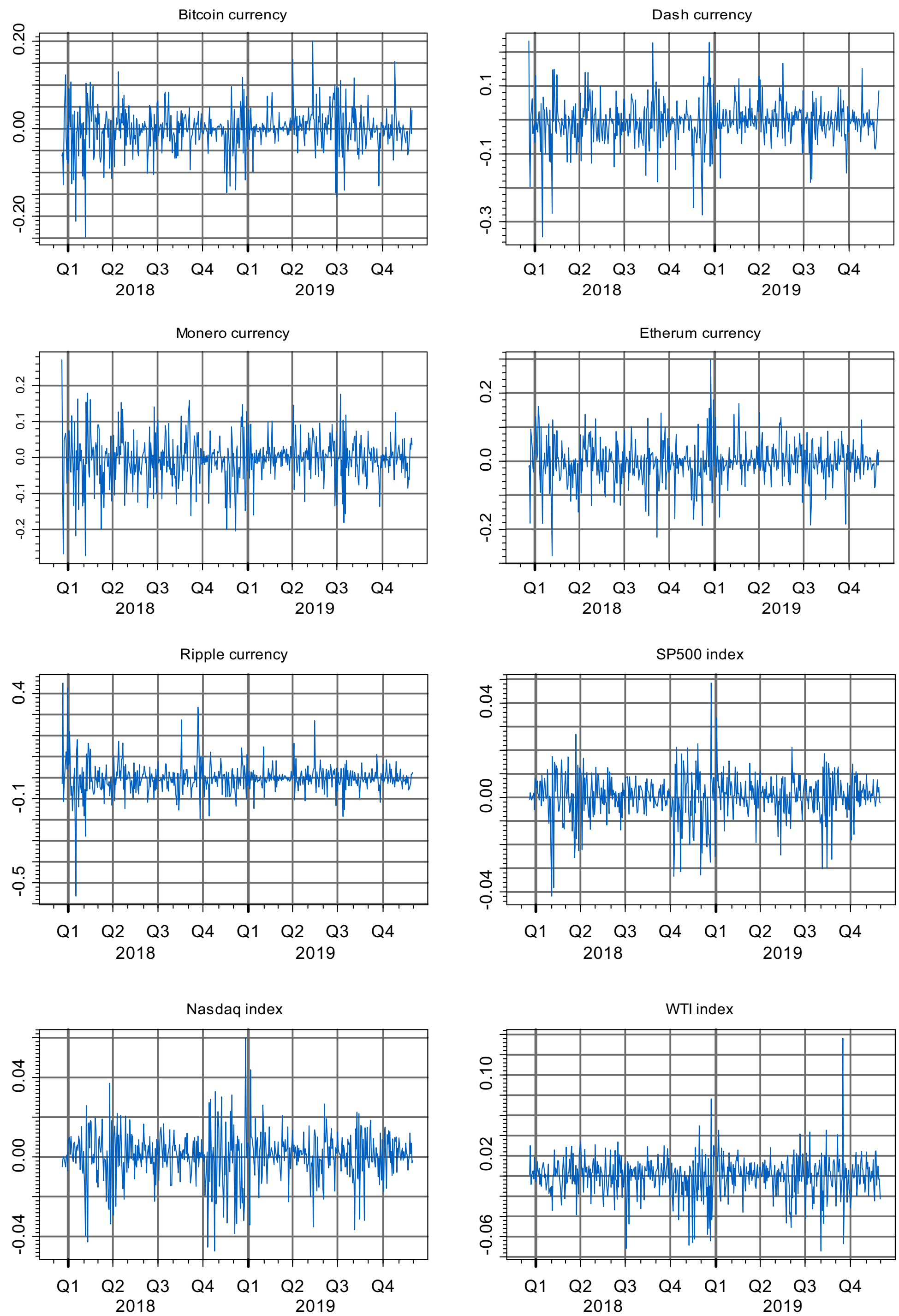


Fig. 1 Evolution of the return indices after the introduction of Bitcoin futures

Stavroyiannis and Babalos (2017), Baur and Dimpfl (2018), (Tiwari et al. 2020), Charfeddine et al. (2019) and Fakhfekh and Jeribi (2020).

The positive (inverted) asymmetric volatility effect holds for the entirety of cryptocurrencies during the three periods. What explains this perhaps puzzling result is that the largest cryptocurrencies are not dominated by uninformed investors but instead by informed investors. Cryptocurrency investors may be less prone to herding and act as contrarians explaining the different estimates and thus behavior of the five crypto-currencies.

If uninformed investors drive up prices due to a fear of missing out in rising markets, volatility will increase by more than in falling markets. If uninformed investors pump up prices as part of a pump and dump scheme, volatility will increase by more than in falling markets. In these

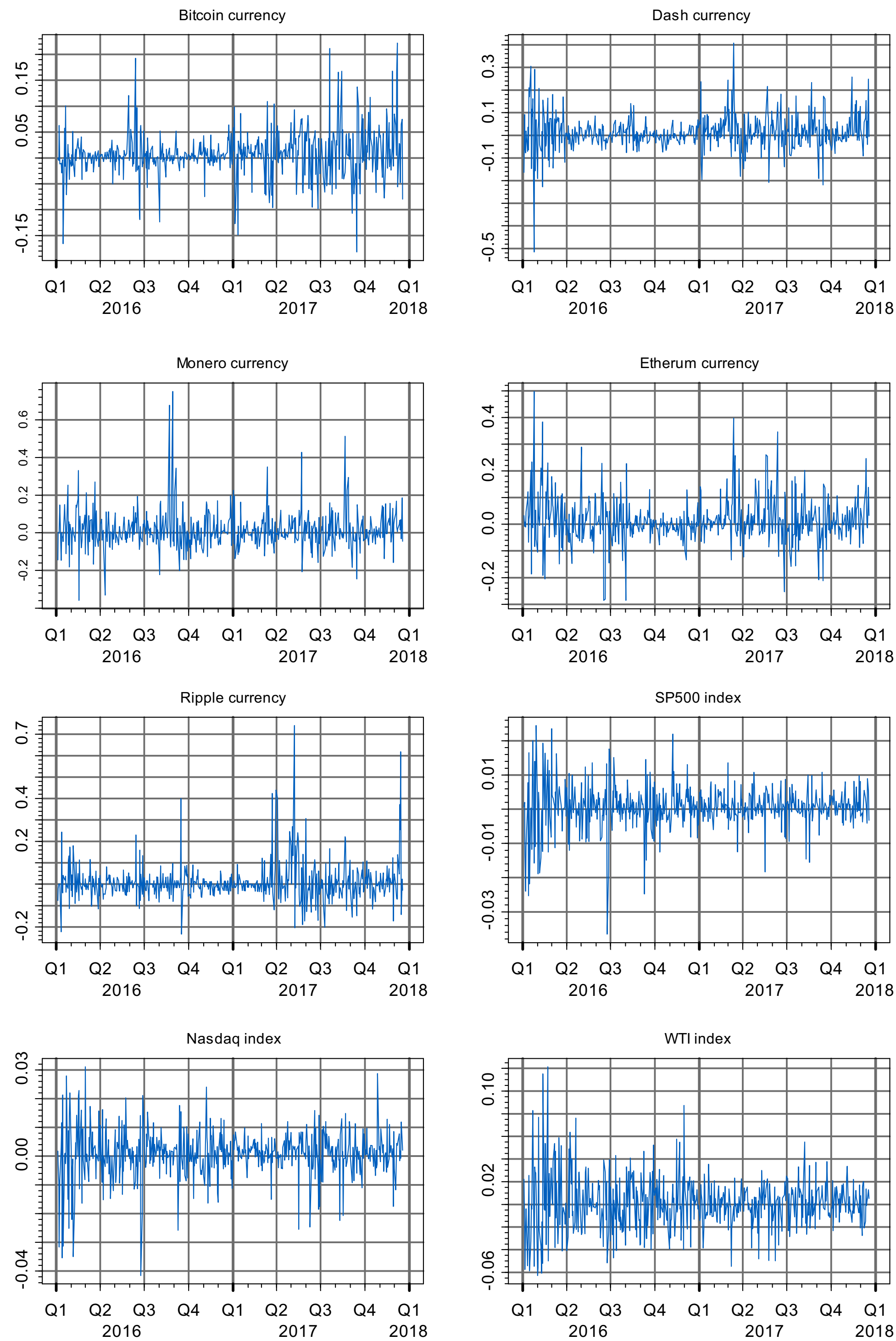
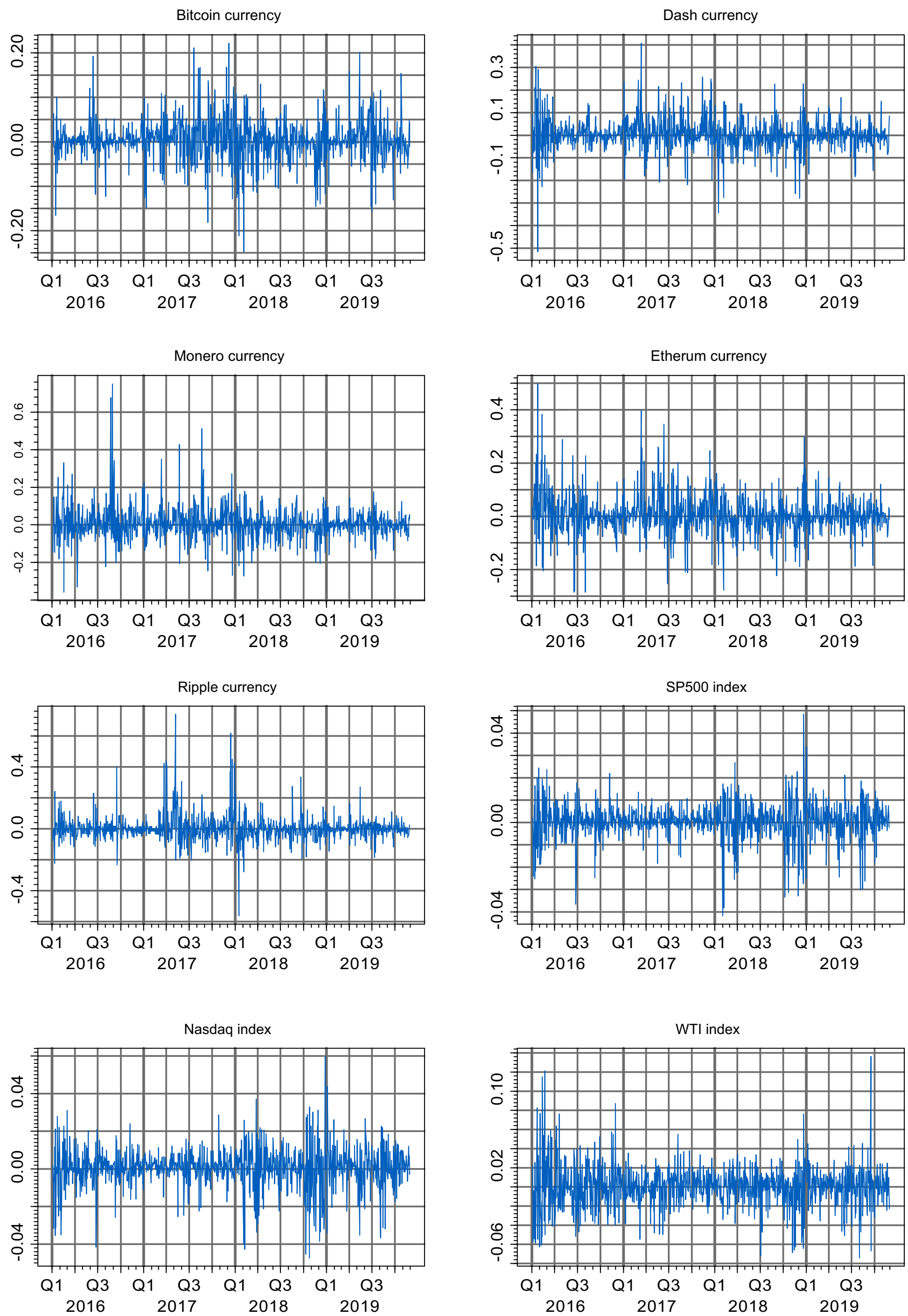


Fig. 2 Evolution of the return indices before the introduction of Bitcoin futures

cases, uninformed investors are driving up prices to levels that are reversed and corrected by informed investors establishing the asymmetric volatility effect. The asymmetry is also consistent with the disposition effect in the absence of informed investors if uninformed investors are more likely to sell in rising markets than in falling markets implying a reversal and higher volatility in rising markets and no reversal and lower volatility in falling markets.

To sum it up, Ethereum, WTI, Nasdaq and S&P 500 indexes appear to demonstrate the persistence of volatility shocks during the period before the introduction of futures (crash 2017), as the persistence degree (d) proves to be

Fig. 3 Evolution of the return indices during the whole period



greater than 0,5. This strong persistence has its explanation in the structural changes likely to be introduced into the variance process (Lamoureux and Lastrapes 1990). In addition, Ripple and Ethereum proved to have a strong persistence during the period after the crash of 2017 while only the ripple presents a persistence of volatility shocks during the whole period. This result confirms that of Charfeddine et al. (2020) who found that Ethereum, WTI, and S&P 500 have high fractional long memory parameters. However, the shock impact on Bitcoin price return volatility proves to be transitory, as the persistence degree coefficient is 0.2811 which is lower than the one observed by the last authors (0.740). This result is similar to that of Klein et al. (2018).

Extreme value theory

After estimating the FIEGARCH model, the model estimation stemming results will be recovered prior to identifying

Table 2 Descriptive statistics

	Period	Mean	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	LM (26)	Q(16)	$Q^2(16)$	R/Smod	Obs.
BITCOIN	Period 1	−0.0016	0.0486	− 0.4102	6.2494	232.122***	53.22***	16.03	55.64***	2.639***	496
	Period 2	0.0072	0.0441	0.3908	7.7550	494.415***	53.54***	16.49	72.02***	1.662*	511
	Period 3	0.0029	0.0465	− 0.0886	7.0140	677.374***	69.127***	21.72	102.06***	2.464***	1007
DASH	Period 1	−0.0060	0.0628	− 0.4992	7.3301	408.094***	52.12***	30.84**	125.78***	2.357***	496
	Period 2	0.0115	0.0759	0.0274	10.1920	1101.359***	85.75***	17.08	54.29***	1.782*	511
	Period 3	0.0029	0.0702	− 0.0892	9.5112	1780.173***	68.68***	40.25***	186.61***	1.608*	1007
ETHEREUM	Period 1	−0.0033	0.0613	− 0.1486	5.7672	160.074***	65.83***	22.06	59.26***	2.035**	496
	Period 2	0.0133	0.0847	0.8813	7.8122	559.215***	40.56**	18.37	36.07***	1.785*	511
	Period 3	0.0051	0.0745	0.7172	8.2746	1253.677***	77.79***	35.83***	122.11***	1.687*	1007
MONERO	Period 1	−0.0037	0.0650	− 0.3090	5.1738	105.555***	118.62***	20.89	120.52***	1.008*	496
	Period 2	0.0127	0.0986	1.9129	14.9917	3373.389***	67.15***	32.67***	77.69***	1.875**	511
	Period 3	0.0046	0.0841	1.6057	15.9358	7453.878***	222.62***	29.66**	225.95***	2.185***	1007
RIPPLE	Period 1	−0.0023	0.0732	0.3225	16.3814	3709.231***	76.55***	31.06**	58.76***	2.224***	496
	Period 2	0.0096	0.0906	2.7104	18.2115	5552.320***	83.92***	42.53***	66.39***	2.077**	511
	Period 3	0.0037	0.0826	1.9645	18.7774	11092.220***	159.26***	43.41***	152.22***	2.709***	1007
WTI	Period 1	−0.0001	0.0194	0.0302	9.4617	862.975***	102.72***	18.89	241.92***	2.673***	496
	Period 2	0.0012	0.0235	0.5915	5.8358	201.018***	24.32	16.59	22.18	1.583*	511
	Period 3	0.0005	0.0216	0.4143	7.2461	785.292***	85.14***	20.49	215.06***	2.833***	1007
S&P 500	Period 1	0.0003	0.0095	−0.6031	6.6692	308.298***	71.73***	30.17**	172.23***	2.304***	496
	Period 2	0.0006	0.0064	−0.5428	7.5980	475.239***	73.38***	25.29*	121.30***	1.659*	511
	Period 3	0.0004	0.0081	−0.6347	7.7808	1026.630***	162.89***	25.25*	325.35***	2.679***	1007
NASDAQ	Period 1	0.0005	0.0125	−0.4133	5.5807	151.759***	54.09***	21.87	102.07***	1.962**	496
	Period 2	0.0007	0.0084	−0.7099	6.9517	375.414***	76.28***	34.01***	142.45***	1.897**	511
	Period 3	0.0006	0.0106	−0.5217	6.6655	609.432***	170.73***	31.74**	359.28***	2.739***	1007

***, **, *indicate that the estimators are significant at 1%, 5% and 10%level, respectively

extreme losses through the application of Extreme-Value Theory. In fact, 30% of the residue series will be taken as outliers, with 15% representing the highest values and 15% the lowest ones. The upper and lower tails' estimation results, as originating from the Generalized Pareto Distribution (GPD), are given by the following table:

As described earlier, the POT method would be deployed using GPD for tail estimation, while choosing 30% of the sample residue. Note that according to Table 4, and regarding upper tail, Dash, Ethereum, S&P 500 and Nasdaq indices tend to exhibit short tailedness, as the values of ξ are discovered to be negative whenever Bitcoin, Monero, Ripple and WTI oil price prove to exhibit long tailedness during the three periods. Regarding the lower tail, Bitcoin, Ethereum, Monero and WTI oil price tends to display short tailedness during the three periods with a negative value, while the Dash, Ripple, S&P 500 and NASDAQ indexes appear to demonstrate heavy tailedness.

Copula estimation results

After obtaining both of the GPD and the residuals' pertaining parameters, we turn to estimate the empirical copula relevant to each of the "cryptocurrencies-stock market index and WTI oil price" pairs. After that, we undertake to compare each empirical copula with the theoretical one, as defined in the earlier section. In Table 5, it is depicted as a summary of the best choice copula labels, estimated parameters, ranking AIC, BIC and HQ results of copulas as fitted for both stock markets' cryptocurrency price.

Table 5 indicates that under the AIC, BIC and HQ criterion, the best fit copula and most appropriate for explaining the dependence structure, during the period after the introduction of futures, binding each cryptocurrency with stock market indices, turns out to be Kimeldorf and Sampson copula for the Bitcoin/Nasdaq, Dash/Nasdaq, Dash/WTI and Ethereum/Nasdaq couples As for Bitcoin/Nasdaq and Ripple/WTI, it proves to be normal copula. Concerning the dependence structure between the Monero/Nasdaq, Monero/WTI and Ripple/Nasdaq couples, the best fit copula is discovered to be Frank, while the BB3 appears to be the best copula fit for explaining the dependence structure prevailing between Ethereum and WTI couple. Indeed, the best copula has been selected on the basis of the lowest AIC, BIC and HQ values.

Table 3 AR(1)-FIEGARCH(1, d, 1) Estimation

		C	AR(1)	A	GARCH(1)	ARCH(1)	LEV(1)	Fraction (d)
Bitcoin	Period 1	−0.00187	0.01135	−0.75820*	0.90150***	0.21910***	−0.01767	0.00000002
	Period 2	0.00607***	−0.03335	−0.47330***	0.95870***	0.31040***	0.06856***	0.00000001
	Period 3	0.00291***	0.00179	−0.33349***	0.77658***	0.26176***	0.02470***	0.28110***
Dash	Period 1	−0.00583**	0.02620	−0.52152***	0.4365**	0.31772***	0.10739***	0.33934***
	Period 2	0.00641***	−0.01381	−0.33619***	0.92544***	0.24881***	0.11372***	0.14815
	Period 3	0.00006	0.00880	−0.32497***	0.57504***	0.35224***	0.03607**	0.43772***
Ethereum	Period 1	−0.00282	0.01307	−0.22278***	−0.51862**	0.21557***	0.07039**	**0.64984*** **
	Period 2	0.00752***	0.06962*	−0.44790***	−0.31735***	0.54212***	0.13401***	**0.61322*** **
	Period 3	0.00199	0.05260*	−0.25121***	0.72476***	0.22184***	0.04619***	0.35400***
Monero	Period 1	−0.00182	−0.07111*	−0.29763***	0.61028***	0.22026***	−0.00054	0.39385***
	Period 2	0.01252***	−0.04166	−0.22350	0.85898***	0.02757*	0.14869***	0.17099
	Period 3	0.00426**	−0.05973**	−0.13695***	0.74078***	0.12020***	0.08049***	0.41401***
Ripple	Period 1	−0.00270	−0.04070	−0.22915***	−0.34404**	0.22553***	0.16189***	**0.63969*** **
	Period 2	−0.00027	−0.15555***	−0.83471***	0.15034*	0.62052***	0.32102***	0.33634***
	Period 3	−0.00262*	−0.10002***	−0.42548***	−0.09861**	0.45328***	0.26006***	**0.50380*** **
WTI	Period 1	0.00006	−0.09232**	−0.19310	0.96512***	0.03621*	−0.09378***	0.07456
	Period 2	0.00100	−0.03590	−0.04258*	0.43182	0.04483*	−0.07562**	**0.84999*** **
	Period 3	0.00033	−0.05341**	−0.15584***	0.98054***	0.06450***	−0.08900***	0.04762
S&P 500	Period 1	0.00044*	0.00108	−0.41746*	0.86558***	0.17554***	−0.21021***	0.22226
	Period 2	0.00053***	−0.12781***	−0.05051**	0.73710***	0.01299*	−0.11027***	**0.57571*** **
	Period 3	0.00059***	−0.08070***	−0.51439***	0.90739***	0.18079***	−0.18314***	0.11888*
Nasdaq	Period 1	0.00056	−0.03594	−0.38135*	0.86657***	0.14569***	−0.18854***	0.21803
	Period 2	0.00117***	−0.07219***	0.03537***	0.38997***	−0.14300***	−0.28101***	**0.62841*** **
	Period 3	0.00076***	−0.06823**	−0.48730***	0.95690***	0.10620***	−0.17440***	0.00000002

Table 6 presents that under the same informational criterion, the best fit copula and most appropriate for explaining the dependence structure, during the period before the introduction of futures, binding each cryptocurrency with stock market indices, turns out to be BB3 copula for the all couples except Ethereum/S&P 500 and Monero/WTI for which the best copula is the Tawn. Concerning the dependence structure between the Ripple/Nasdaq couple, the best fit copula is Frank.

According to Table 7, the best fit copula and most appropriate to explain the dependence structure, during the whole period, binding each cryptocurrency with stock market indices turns out to be BB3 copula for all the couples.

Implications for portfolio management and hedging performances

This section is devoted to assessing the implications of the cryptocurrency market–stock market indices interdependence in terms of optimal portfolio design, oil risk hedging, and risk. An analysis of the cryptocurrency and stock market index portfolios seems crucial, in this respect, as it has critical relevance to cryptocurrency investors as well as to risk management, as induced by cryptocurrency price fluctuations. Table 8 is a highlight of the hedging strategy result effectiveness, as estimated for each cryptocurrency with stock market indices portfolios. In order to compare the results of the hedging effectiveness estimated from the FIEGARCH-EVT-copula model, we also introduce the results estimated through the OLS regression. Using this last regression, the hedge ratio and hedging effectiveness can be examined by assessing regression coefficient and R-square.

This regression is just a linear regression of change in spot prices on change in futures prices. Let Y_t and X_t be logged financial asset returns and cryptoasset returns, respectively. The one period minimum variance constant hedge ratio can be estimated from the expression:

$$Y_t = c + \beta * X_t + \varepsilon_t \qquad (6)$$

where ε_t is the error term from OLS estimation, Y_t and X_t represent financial asset returns and cryptoasset returns, respectively. The minimum hedge ratio β^* is the slop of equation. The R-square of this model indicates the hedging effectiveness.

As can be noticed, the dependence between each cryptocurrency and conventional assets seems less remarkably

Table 4 Generalized Pareto Distribution estimated tails

Variable	Period	Upper tail		Lower tail	
		ξ	β	ξ	β
Bitcoin	Period 1	0.2456	0.5114	– 0.0238	0.7679
	Period 2	0.1554	0.7259	– 0.0127	0.8828
	Period 3	0.255	0.571	– 0.0248	0.8105
Dash	Period 1	– 0.0476	0.6904	0.2019	0.6225
	Period 2	– 0.0952	0.8208	0.0861	0.4890
	Period 3	– 0.0111	0.7271	0.1719	0.5925
Ethereum	Period 1	– 0.1000	0.7819	– 0.1514	0.9386
	Period 2	– 0.0150	0.9046	– 0.1108	0.5175
	Period 3	– 0.0341	0.8566	– 0.0590	0.7902
Monero	Period 1	0.0081	0.6214	– 0.2831	1.0653
	Period 2	0.2632	0.6610	– 0.0352	0.5726
	Period 3	0.2673	0.5169	– 0.0529	0.7163
Ripple	Period 1	0.3168	0.6869	0.0093	0.7630
	Period 2	0.1582	0.8962	0.1117	0.4012
	Period 3	0.2142	0.7992	0.1241	0.5062
WTI	Period 1	0.2366	0.3918	– 0.0354	0.7609
	Period 2	0.0758	0.6769	– 0.1054	0.6137
	Period 3	0.1206	0.5119	– 0.0957	0.7497
S&P 500	Period 1	– 0.1799	0.4986	0.0216	0.7306
	Period 2	– 0.0266	0.4637	0.0011	0.9082
	Period 3	– 0.1026	0.5181	0.0487	0.7695
Nasdaq	Period 1	– 0.4717	0.6186	0.1354	0.8187
	Period 2	– 0.1466	0.5511	0.0558	0.8652
	Period 3	– 0.0792	0.4718	0.0069	0.8393

The table shows estimated parameters for the entirety of indices using generalized Pareto distribution (GPD). Also note that βand ξis the shape and scale parameters of the fitted GPD, respectively. Period 1, Period 2 and Period 3 design the period after the introduction of future, the period before the introduction of future and the total period, respectively

strong. This result is confirmed by both, the Correlation coefficients and the Kendall Tau.

Table 8 summarizes the values of the hedge ratios β between cryptocurrency markets and conventional assets based on the FIEGARCH-EVT-Copula model and OLS regression. The results that prove no copula explaining the structural dependence between cryptocurrency markets and conventional assets are detected, because there is no convergence of the copula model between these pairs since there are negative dependence structures.

From this, we observe also from the results that the model report very low values of hedging ratio for the majority of pairs, less than 3.13%, and positive values for the all-pairs except for WTI–Bitcoin (period 1, total period), WTI–Dash and WTI–Ethereum pairs which the values of their hedging ratio exceed 4.24%. Indeed, the findings indicate that the OLS regression report also very low values of hedging ratio for the entirety of pair series, less than 3.91%. These results have an important implication. In addition, the low values of the hedge ratios suggest that the investment risk of conventional financial assets can be hedged by taking short positions in the cryptocurrencies market. For instance, a one-dollar long position on the S&P 500 should be hedged by going short 0.007 USD on Monero.

Overall, we found out that to minimize the risk while keeping the same expected returns of the digital-conventional financial asset portfolio, the investor should hold more conventional financial assets than digital assets except for WTI–Bitcoin (period 1, total period), WTI–Dash and WTI–Ethereum pairs which the values of their hedging ratio are rather important (5%). This empirical finding can be explained by the low dependence between returns of the digital and conventional assets, as well as by the high volatility that characterizes

Table 5 Dependence between indices after the introduction of Bitcoin futures

Variable	Copula name	Copula parameters		Dependence coefficients		Tail index		Information criteria		
		δ	θ	τ	P	Upper	Lower	AIC	BIC	HQ
Bit/Nasdaq	Kimeldorf and Sampson	0.0477 (0.0466)	–	0.0233	0.0349	–	–	0.803	5.009	2.454
Bit/WTI	Normal	0.0555 (0.0441)	–	0.0353	0.0530	0	0	0.428	4.664	2.089
Dash/Nasdaq	Kimeldorf and Sampson	0.0256 (0.0456)	–	0.0127	0.0189	–	–	1.659	5.866	3.311
Dash/WTI	Kimeldorf and Sampson	0.0125 (0.0457)	–	0.0062	0.0093	–	–	1.922	6.129	3.573
Ether/Nasdaq	Kimeldorf and Sampson	0.0782 (0.0493)		0.0376	0.0564	–	–	– 1.007	3.198	0.643
Ether/WTI	BB3	0.0779 (0.0452)	1.0645 (0.0269)	0.0963	0.1431	0.0823	1	– 4.724	3.689	– 1.421
Monero/nasd	Frank	0.1947 (0.2685)	–	0.0216	0.0324	–	–	1.474	5.680	3.125
Monero/WTI	Frank	0.2602 (0.2701)	–	0.0289	0.0433	–	–	1.071	5.278	2.723
Rip/Nasdaq	Frank	0.2458 (0.2650)	–	0.0273	0.0409	–	–	1.139	5.345	2.790
Rip/WTI	Normal	0.0130 (0.0449)	–	0.0083	0.0124	0	0	1.916	6.122	3.567

Table 6 Dependence between indices before the introduction of Bitcoin futures

Variable	Copula name	Copula parameters					Dependence coefficients		Tail index		Information criteria		
		δ	Θ	α	β	r	T	ρ	Upper	Lower	AIC	BIC	HQ
Bitcoin/WTI	BB3	0.0882 (0.0434)	1.0539 (0.0254)				0.0916	0.1365	0.0697	1	− 5.301	3.172	− 1.979
Dash/S&P 500	BB3	0.0475 (0.0402)	1.0851 (0.0258)				0.1003	0.1489	0.1058	1	− 10.127	− 1.655	− 6.806
Dash/Nasdaq	BB3	0.0682 (0.0426)	1.0744 (0.0265)				0.1004	0.1493	0.0937	1	− 6.741	1.732	− 3.419
Dash/WTI	BB3	0.0468 (0.0413)	1.0501 (0.0262)				0.0697	0.1039	0.0650	1	− 0.738	7.734	2.583
Ethereum/S&P 500	Tawn			0.0066 (0.0059)	1.0000 (0.8803)	27.4730 (15.3596)	5.2e− 9	0.0099	0.0066	0	− 2042.203	− 2037.967	− 2040.543
Ethereum/Nasdaq	BB3	0.0632 (0.0426)	1.0560 (0.0266)				0.0824	0.1226	0.0721	1	− 2.396	6.077	0.926
Monero/S&P 500	BB3	0.0353 (0.0421)	1.0651 (0.0261)				0.0777	0.1157	0.0829	1	− 3.364	5.109	− 0.0421
Monero/Nasdaq	BB3	0.1024 (0.0448)	1.0649 (0.0270)				0.1072	0.1593	0.0827	1	− 7.079	1.393	− 3.758
Monero/WTI	Tawn			0.0525 (0.0353)	0.0262 (0.0176)	46.9796 (30.8007)	0.0178	0.0264	0.0262	0	1.447	5.684	3.108
Ripple/Nasdaq	Frank			0.1750 (0.1591)	0.0099 (0.0080)	10.7652 (7.1416)	0.0095	0.0141	0.0099	0	1.507	5.743	3.167

Table 7 Dependence between indices during the total period

Variable		Copula parameters		Dependence coefficient		Tail index		Information criteria		
		δ	θ	τ	ρ	Upper	Lower	AIC	BIC	HQ
Bitcoin/Nasdaq	BB3	0.0532 (0.0304	1.0474 (0.0189)	0.0702	0.1047	0.0617	1	− 4.787	5.043	− 1.052
Bitcoin /WTI	BB3	0.0703 (0.0312)	1.0469 (0.0185)	0.0775	0.1156	0.0611	1	− 7.897	1.933	− 4.162
Dash/S&P 500	BB3	0.0136 (0.0289)	1.0523 (0.0178)	0.0562	0.0839	0.0677	1	− 6.269	3.560	− 2.534
Dash/Nasdaq	BB3	0.0485 (0.0301)	1.0608 (0.0186)	0.0799	0.1191	0.0779	1	− 9.584	0.245	− 5.849
Dash/WTI	BB3	0.0376 0.0302)	1.0417 (0.0188)	0.0578	0.0864	0.0547	1	− 2.096	7.734	1.639
Ethereum/Nasdaq	BB3	0.0696 (0.0309)	1.0492 (0.0191)	0.0793	0.1182	0.0640	1	− 7.167	2.663	− 3.432
Monero/S&P 500	BB3	0.0108 (0.0296)	1.0424 (0.0184)	0.0458	0.0684	0.0555	1	− 1.769	8.059	1.965
Monero/Nasdaq	BB3	0.0481 (0.0303)	1.0560 (0.0191)	0.0755	0.1125	0.0722	1	− 6.829	3.001	− 3.094
Monero/WTI	BB3	0.0416 (0.0305)	1.0530 (0.0185)	0.0698	0.1042	0.0685	1	− 6.189	3.641	− 2.454
Ripple/Nasdaq	BB3	0.0124 (0.0293)	1.0497 (0.0187)	0.0532	0.0795	0.0645	1	− 3.682	6.147	0.0524

BB3 is the fitted copula name. Standard errors are placed in parentheses

digital asset prices. These results imply that adding a very small portion of digital assets to a diversified portfolio of conventional financial assets will substantially reduce its overall risk (less than 0, 051%) for a given level of expected return.

With respect to OLS regression, the FIEGARCH-EVT-copula model is the most suitable technique to provide higher return and low risk in all series pairs. Indeed, the results also prove that the S&P 500 and Nasdaq indices can be hedged by Monero during the period before the crash (the introduction of futures) and during the total period while the Nasdaq is hedged by Bitcoin during the period after the crash. Bitcoin is the best hedging instrument for crude oil during the period before and after the crash while Dash is the best hedging instrument for the total period.

Regarding the hedging effectiveness, we observe that hedging strategies involving digital and conventional financial assets moderately reduce the portfolio's risk (variance) in the case of Ethereum–Nasdaq, with a variance reduction ranging from 3.5 to 9.16% when we calculate the variance during the total period.

For the rest of the pairs, cryptocurrencies appear to be a poor hedging instrument, as the HE index is always below 0.99% as well as for those detected through OLS regression. These empirical findings confirm some previous studies of the hedging capabilities of cryptocurrencies (see, for instance, Guesmi et al. (2019), and Corbet et al. (2018a; b)). Overall, the results show that digital assets are, in most cases, better diversifier instruments.

The results have founded to be very interesting in order to, firstly, help investors making the right decision about the optimal choice of portfolio assets based on the nonlinear structure of dependence between the cryptocurrency markets and conventional financial assets detected among the copula theory and secondly, to obtain the optimal strategy of hedging. This approach (FIEGARCH-EVT-Copula) is very attractive in order to reduce the risk of portfolio losses.

Conclusion

The present paper investigates the nonlinear relationship between the cryptocurrency market and conventional financial assets (S&P 500, Nasdaq and WTI). In particular, we investigate the economic and financial benefits of five digital assets (Bitcoin, Dash, Ethereum, Monero and Ripple) for financial investors. To do so, we assess the capabilities of cryptocurrencies to generate benefits from portfolio diversification as well as hedging strategies. Four important conclusions are drawn from this study. First, using FIEGARCH-EVT-Copula models, the WTI, NASDAQ and S&P 500 returns, during the three periods, highlight the persistence of a negative and significant leverage effect while the cryptocurrency markets present a positive asymmetric volatility

Table 8 Hedging results estimation

		FIEGARCH-EVT-copula regression						OLS regression			
	Period	*Kend*	*Corr.*	*β*	*Mean*	*Var.*	HE	*B*	HE	*Mean*	*Var.*
S&P 500/ Bitcoin	Period 2	No copula that explain the structural dependence between Bitcoin and S&P 500						0.00103	0.000049	0.00051	0.000087
	Period 1							0.01337	0.004718	0.00057	0.000090
	T. Period							0.00738	0.001814	0.00061	0.000081
S&P 500/ Dash	Period 2	No copula that explain the structural dependence between Dash and S&P 500						0.01416	0.027787	0.00037	0.000055
	Period 1	0.1003	0.1568	0.01623	0.00044	0.00004	0.0021	0.01321	0.007690	0.00039	0.000045
	T. Period	0.0562	0.0882	0.01085	0.00045	0.00007	0.0039	0.00339	0.000876	0.00043	0.000068
S&P 500/ Ethereum	Period 2	No copula that explain the structural dependence between Ethereum and S&P 500						0.00518	0.004640	0.00051	0.000051
	Period 1	$5.2.10^{-9}$	$8.2.10^{-9}$	$6.4.10^{-10}$	0.00056	0.00004	0.0036	0.00349	0.000513	0.00054	0.000039
	T. Period	No copula that explain the structural dependence between Ethereum and S&P 500						0.00437	0.001633	0.00056	0.000054
S&P 500/ Monero	Period 2	No copula that explain the structural dependence between Monero and S&P 500						0.00053	0.001594	0.00039	0.000041
	Period 1	0.0777	0.1217	0.00759	0.00046	0.00004	0.0002	0.00703	0.002333	0.00044	0.000038
	T. Period	0.0458	0.0719	0.00722	0.00043	0.00007	0.0001	0.00010	0.000001	0.00042	0.000063
S&P 500/ Ripple	Period 2	No copula that explain the structural dependence between Ripple and S&P 500						0.00180	0.000643	0.00040	0.000039
	Period 1							0.00105	0.000066	0.00041	0.000041
	T. Period							0.00139	0.000205	0.00039	0.000042
Nasdaq/Bitcoin	Period 2	0.0233	0.0365	0.00931	0.00053	0.00016	0.0021	0.00448	0.000553	0.00052	0.000170
	Period 1	No copula that explain the structural dependence between Bitcoin and Nasdaq						0.00251	0.000095	0.00053	0.000060
	T. Period	0.0702	0.1101	0.02612	0.00057	0.00011	0.0022	0.00091	0.000016	0.00055	0.000120
Nasdaq/ Dash	Period 2	0.0127	0.0199	0.00393	0.00054	0.00016	0.0051	0.01493	0.018177	0.00052	0.000180
	Period 1	0.1004	0.1571	0.01966	0.00055	0.00006	0.0096	0.00239	0.000145	0.00053	0.000060
	T. Period	0.0799	0.1252	0.02051	0.00062	0.00011	0.0099	0.00434	0.004342	0.00060	0.000110
Nasdaq/Ethereum	Period 2	0.0376	0.0591	0.01152	0.00055	0.00016	0.0526	0.00038	0.000014	0.00055	0.000170
	Period 1	0.0824	0.1290	0.01237	0.00056	0.00006	0.0348	0.00889	0.001903	0.00056	0.000061
	T. Period	0.0793	0.1242	0.01811	0.00057	0.00011	0.0916	0.00288	0.000408	0.00055	0.000121
Nasdaq/Monero	Period 2	0.0216	0.0339	0.00659	0.00054	0.00015	0.0040	0.00278	0.001069	0.00053	0.000143
	Period 1	0.1072	0.1677	0.01307	0.00055	0.00006	0.0017	0.00105	0.000030	0.00054	0.000059
	T. Period	0.0755	0.1184	0.01581	0.00058	0.00011	0.0014	0.00176	0.000194	0.00057	0.000111
Nasdaq/Ripple	Period 2	0.0273	0.0429	0.00825	0.00052	0.00016	0.0061	0.00094	0.000102	0.00050	0.000167
	Period 1	0.0095	0.0148	0.00156	0.00072	0.00006	0.0038	0.00895	0.002741	0.00069	0.000059
	T. Period	0.0532	0.0836	0.01272	0.00061	0.00011	0.0043	0.00412	0.001026	0.00058	0.000101
WTI/Bitcoin	Period 2	0.0353	0.0555	0.02349	− 0.00003	0.00038	0.0033	0.02768	0.002692	− 0.00002	0.000365
	Period 1	0.0916	0.1435	0.09649	0.00069	0.00051	0.0028	0.00374	0.000087	0.00065	0.000499
	T. Period	0.0775	0.1215	0.06252	0.00041	0.00045	0.0084	0.01586	0.001168	0.00041	0.000439
WTI / Dash	Period 2	0.0062	0.0098	0.00325	− 0.00006	0.00038	0.0045	0.03907	0.015886	− 0.00007	0.000359
	Period 1	0.0697	0.1092	0.04243	0.00079	0.00051	0.0068	− 0.01075	0.001210	0.00076	0.000498
	T. Period	0.0578	0.0908	0.03124	0.00051	0.00045	0.0029	0.01997	0.004222	0.00050	0.000441
WTI/ Ethereum	Period 2	0.0963	0.1506	0.04954	0.00011	0.00039	0.0075	− 0.02403	0.007489	0.00009	0.000390
	Period 1	No copula that explain the structural dependence between Ethereum and WTI						0.01477	0.002177	0.00008	0.000432
	T. Period							− 0.00989	0.001166	0.00011	0.000386
WTI/Monero	Period 2	0.0289	0.0454	0.01479	− 0.00002	0.00038	0.0035	0.00028	0.000001	− 0.00004	0.000376
	Period 1	0.0178	0.0279	0.00659	0.00107	0.00050	0.0052	− 0.00165	0.000030	0.00110	0.000499
	T. Period	0.0698	0.1096	0.02995	0.00045	0.00045	0.0033	0.00043	0.000003	0.00045	0.000445

Table 8 (continued)

		FIEGARCH-EVT-copula regression						OLS regression			
	Period	*Kend*	*Corr.*	*β*	*Mean*	*Var.*	HE	*B*	HE	*Mean*	*Var.*
WTI/Ripple	Period 2	0.0083	0.0130	0.00425	− 0.00007	0.00038	0.0073	− 0.00382	0.000217	− 0.00009	0.000381
	Period 1	No copula that explain the structural dependence between Ripple and WTI						0.00258	0.000095	0.00011	0.000571
	T. Period							− 0.00079	0.000009	0.00087	0.000432

effect. This inverted asymmetric effect can be explained with the herding of uninformed investors if prices go up and contrarian behavior of informed investors if prices go down.

Secondly, Ethereum, WTI, NASDAQ and S&P 500 indexes appear to demonstrate the persistence of volatility shocks during the period before the introduction of futures (crash 2017). In addition, Ripple and Ethereum proved to have a strong persistence during the period after the crash of 2017 while only the Ripple presents a persistence of volatility shocks during the whole period. Thirdly, we find evidence of a dependence structure between all the different pairs considered and during the three periods. In addition, we show that for the case of a portfolio with mixed assets, the level of dependence is very weak for all the seven examined pairs without exception, a result which suggests that cryptocurrencies can offer new opportunities for portfolio diversification. Finally, we find that to minimize the risk while keeping the same expected returns of the digital-conventional financial asset portfolio, the investor should hold more conventional financial assets than digital assets except for WTI–Bitcoin (period 1, total period), WTI–Dash and WTI–Ethereum pairs which the values of their hedging ratio are rather important (5%). Furthermore, the FIEGARCH-EVT-copula is the best model to analyze the hedging strategy en term of return and risk compared to OLS regression.

The results of this study have several important implications for investors, market analysts and participants. In addition to helping shed more light on the nature of cryptocurrencies, this study provides a better representation of the dependence between digital and conventional financial assets, which is a key insight for investors and portfolio managers seeking to minimize the risk of their portfolio without compromising the returns.

Practically, we show in this paper that some successful diversification strategies might be identified, and investors will benefit from the diversification capabilities of cryptocurrencies. Despite the several results of this study that contribute to a better understanding of cryptocurrencies and their financial potential, some shortcomings related to the nature of the digital assets are worth mentioning. First, to explore the potential hedging of cryptocurrencies, we used the spot prices. The nascent future market of cryptocurrencies is a new tool at the disposition of investors not only to hedge cryptocurrencies themselves but also it can be used to hedge other financial assets. However, these markets are still not mature, as the first introduction of Bitcoin futures in the CBOE exchange in Chicago was current.

The copula theory has been frequently used to model the dependence structure between markets and to get rid of restrictive assumptions. This theory overcomes the two drawbacks in Markowitz's model which are: the normality of the return distribution and the use of the Pearson correlation coefficient. This one supposes the linearity of the dependency structure between the asset components of the portfolio, which is not the case in the copula theory that is based on a nonlinear dependence structure between two assets. Thus, this approach allows us to calculate a correlation coefficient based on a nonlinear dependence structure pulled from the calculation of Kendall's tau.

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Ahmed Jeribi holds a PhD in Finance. He is currently an Assistant Professor in Finance at the University of Monastir-Tunisia. His main research interests are related to corporate governance, finance and financial econometrics and copula theory.

Mohamed Fakhfekh received his PhD in Finance at the Faculty of Economics and Management of Sfax. He is currently an Assistant Professor in Finance at the University of Sfax-Tunisia. His main research interests are related to financial markets, Islamic and conventional finance, and financial econometrics and copula theory.