Pacific-Basin Finance Journal 74 (2022) 101822

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Nonlinear dependence and spillovers between cryptocurrency and global/regional equity markets[☆]

Waqas Hanif[a,b], Jose Areola Hernandez[c], Victor Troster[d], Sang Hoon Kang[e], Seong-Min Yoon[f,*]

[a] CEFAGE - Center for Advanced Studies in Management and Economics, University of Algarve, Portugal
[b] Department of Management Sciences, COMSATS University Islamabad, Attock Campus, Pakistan
[c] Independent Researcher, Los Angeles, California, USA
[d] Department of Applied Economics, Universitat de les Illes Balears, Palma de Mallorca, Spain
[e] Department of Business Administration, Pusan National University, Busan, Republic of Korea
[f] Department of Economics, Pusan National University, Busan, Republic of Korea

A R T I C L E I N F O

JEL classification:
C58
D85
F36
G11
G21

Keywords:
Cryptocurrency
Copula
Conditional value-at-risk
Equity market
Nonlinear dependence
Spillover

A B S T R A C T

In this paper, we investigate the nonlinear dependence dynamics among eight cryptocurrencies (Monero, Bitcoin, Dash, Litecoin, Stellar, XRP, Ethereum, and Nem) by applying time-varying copulas. We also examine the upside and downside spillovers between cryptocurrencies and equity markets by a conditional Value-at-Risk (CoVaR) approach. We show that the dynamics of dependence of the portfolio of cryptocurrencies reveal both symmetric and asymmetric features, with the symmetric dynamics being more predominant. NEM and Ethereum have the largest downside and upside CoVaR spillovers on the world equity index, respectively. The largest downside CoVaR spillovers from the world equity index are to NEM followed by Stellar, and the largest upside spillovers are to Ethereum followed by NEM. Stellar and Bitcoin exhibit the largest downside and upside CoVaR spillovers on the Americas equity index. The largest downside CoVaR spillovers from the Americas equity index are to Stellar and NEM, and those on the upside are to Ethereum and NEM. In addition, we find that most cryptocurrencies exhibit safe haven or hedge properties more often than rare metals and diamonds for daily equity indices. Finally, we conduct an out-of-sample analysis of optimal-weighting portfolio strategies based on C-vine copulas using cryptocurrencies and equity indices that entails forward-looking measures of risk that are economically significant, which outperform benchmark strategies.

1. Introduction

In recent years, cryptocurrencies such as Bitcoin, Litecoin, Ripple, and Ethereum have drawn much attention in the popular

☆ Waqas Hanif acknowledges financial support from Fundação para a Ciência e a Tecnologia (Grant UIDP/04007/2020). Victor Troster acknowledges financial support by Spain's Ministerio de Ciencia e Innovación (grant number PID2020-114646RB-C43). Seong-Min Yoon acknowledges financial support by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2020S1A5B8103268).

* Corresponding author at: Busandaehak-ro 63beon-gil, Geumjeong-gu, Busan 46241, Republic of Korea.
E-mail addresses: waqashanif085@gmail.com (W. Hanif), victor.troster@uib.es (V. Troster), sanghoonkang@pusan.ac.kr (S.H. Kang), smyoon@pusan.ac.kr (S.-M. Yoon).

https://doi.org/10.1016/j.pacfin.2022.101822
Received 9 October 2020; Received in revised form 4 July 2021; Accepted 16 July 2022
Available online 22 July 2022
0927-538X/

financial press and in the investment management community. Although cryptocurrency is designed as an innovative payment system based on underlying block chain technology without any government intervention, it is utilized for speculation instead of as a medium of exchange or as an alternative currency (Baur et al., 2018b). Cryptocurrency plays an important role as an alternative investment asset in international portfolio management (Dyhrberg, 2016a). The total cryptocurrency market cap experienced an enormous growth in recent years, and it was one of the dominant topics in financial headlines by the end of 2017. As of December 2017, the cryptocurrency market had a capitalisation of more than $800 billion with 1373 different cryptocurrencies available worldwide (https://coinmarketcap.com/).

Certain technologists are enthusiastic about the potential of cryptocurrencies to increase trades, by reducing the costs and payment uncertainties of financial intermediation, and to serve as a store of value from inflation taxes. Although blockchains still face some issues in authenticating the validation process, the exchange, resolution, and supervision process of blockchains are achieving "institutional robustness" (Low and Marsh, 2019). Besides, Bitcoin has some similarities with gold since the supply of Bitcoin is algorithmically restricted; in addition, Bitcoin has a convenience yield because it acts as a medium-of-exchange. Conversely, detractors of cryptocurrencies argue that the equilibrium price of Bitcoin would be zero if its use for criminal transactions was ceased, and they regard the decentralized technology of blockchains as slow and clumsy (Marsh and Low, 2019). Bitcoin prices are highly volatile so that it makes it difficult for economic agents to price their services or products in it, which discourages its application as a medium-of-exchange. Nevertheless, Marsh and Low (2019) argue that the volatility of the price of Bitcoin may stabilize over time due to the introduction of innovations in cryptocurrency technologies, increasing the use of cryptocurrencies as a means of currency. This may lead to the fading of the use of fiat currencies that are very weak or that belong to countries with strict capital controls.

Among cryptocurrencies, Bitcoin remains the largest and leading entity, capturing >50% of coin market capitalization (Al-Yahyaee et al., 2019). Market capitalization and turnover of cryptocurrency have been exponentially increasing (Charfeddine et al., 2020). Furthermore, the cryptocurrency market, including Bitcoin, has introduced a new type of funding mechanism, referred as initial coin offerings (ICOs), which has attracted large amounts of money. According to the Coin Schedule report, in 2017, 366 ICOs raised USD 6.2 billion, while 254 ICOs raised USD 7.8 billion (Fisch, 2019). Nevertheless, empirical analyses have shown that the behaviour of cryptocurrencies differs from that of traditional currencies and commodities with different types of maturity, operating system, valuation, underlying assets, and speculation (Yermack, 2015; Mensi et al., 2019). Due to their limited co-movement with conventional investment assets (stocks, exchange rates, and bonds), cryptocurrencies offer opportunities for portfolio diversification (Ji et al., 2018; Al-Yahyaee et al., 2019; Guesmi et al., 2019; Kajtazi and Moro, 2019).

With the growing emphasis on cryptocurrency as an alternative financial instrument, financial analysts believe that the burgeoning global cryptocurrency growth is merely a reflection of investor's faith in this cryptocurrency as a hedging asset. Like gold, recent extreme market turmoil has also motivated investors to pursue an effective hedging asset or a safe-haven asset beyond traditional investments such as stocks and bonds (Klein et al., 2018; Shahzad et al., 2019). Currently, these cryptocurrencies are an alternative to mainstream currencies and an economic safe haven beyond the regulatory and institutional supervision of the mainstream financial sector. The literature emphasizes the important role of Bitcoin for diversification and hedging against the risk of other asset classes during extreme downside risk (Bouri et al., 2017a; Bouri et al., 2017b; Smales, 2019). Bouri et al. (2017b) found that safe-haven and hedge capabilities of Bitcoin with respect to commodities only occurred during the 2013 pre-crash period, whereas Bitcoin has no longer served as a diversifier during the post-crash period. However, the cryptocurrency market is still in its infancy, showing features such as price clustering (Urquhart, 2016), leverage, heavy-tailedness, stochastic volatility, and long memory (Phillip et al., 2018). Furthermore, while some studies have investigated dependence or co-movement between multiple cryptocurrencies and Bitcoin (Antonakakis et al., 2019; Beneki et al., 2019; Bouri et al., 2020c), little attention has been paid to the extreme risk spillover among cryptocurrency markets. Analysing the extreme downside and upside risk among cryptocurrency markets can help us understand the co-movement, risk spillover, and hedging strategies for cryptocurrency portfolios (Tiwari et al., 2020).

In this paper, we analyse the nonlinear dependence dynamics between cryptocurrencies and the risk spillovers between cryptocurrency and equity markets. More specifically, we investigate the symmetric and asymmetric dynamics of dependence between eight cryptocurrencies — namely Monero, Bitcoin, Dash, Litecoin, Stellar, XRP, Ethereum, and NEM — by employing a wide array of dynamic bivariate copula specifications. Copulas are a popular tool to measure dependence risk between financial time series because their flexibility allows for the representation of diverse joint distributions. In addition, we assess the presence of risk spillover effects between the cryptocurrencies considered and four MSCI equity market indices (World, America, Europe, and Asian Pacific regions) by quantifying the upside and downside conditional Value-at-Risk (CoVaR) measure, designed to measure the risk of extreme losses under the Value-at-Risk (VaR) of another market.

Our motivation for considering eight cryptocurrencies and four global and regional equity markets is that we can provide a broader and more relevant analysis across a wider array of cryptocurrency assets and equity markets. For international portfolio investors is relevant to know how each cryptocurrency affects (and is affected by) each of the equity markets under consideration, as it broadens their investment and diversification horizon. Further, understanding asymmetric dependence dynamics among cryptocurrencies and the risk spillovers between cryptocurrencies and equity markets is useful for international portfolio design.

The contributions of this paper to the relevant literature are as follows. First, it uniquely considers global and regional equity markets in the analysis of downside and upside spillovers between cryptocurrencies and equity markets, thus not focusing only in a specific equity market. Besides, the obtained empirical and original results indicate that the dependence dynamics of the portfolio of cryptocurrencies exhibit both symmetric and asymmetric features, with the symmetric dynamics being predominant. The largest downside and upside CoVaR spillovers on the world equity index are from NEM and Ethereum, respectively. The largest downside CoVaR spillovers from the world equity index are to NEM followed by Stellar, and the largest upside spillovers from the world equity index are to Ethereum followed by NEM. The largest downside and upside CoVaR spillovers on the Americas equity index are from

Stellar and Bitcoin, respectively. The largest downside CoVaR spillovers from the Americas equity index are to Stellar and NEM, and the greatest upside spillovers from the Americas index are to Ethereum and NEM. The largest downside CoVaR spillovers on the Europe equity index are from Bitcoin, Litecoin, and Ethereum, whereas the greatest upside spillovers are from Litecoin and Ethereum. The largest downside CoVaR spillovers from the Europe equity index are to NEM and Stellar, while the biggest upside spillovers from the Europe index are to Ethereum and NEM. The largest downside CoVaR spillovers on the Asia Pacific equity index are from Stellar and Monero, and the greatest upside spillovers are from Bitcoin and Ethereum. Finally, the largest downside CoVaR spillovers from the Asia Pacific equity index are to Stellar and Monero, while the largest upside spillovers are to Ethereum and NEM.

In addition, we verify the safe-haven and hedge properties of the eight cryptocurrencies with respect to each equity index. Following the approach of Baur and Lucey (2010), Baur and McDermott (2010), Ciner et al. (2013), and Dyhrberg (2016a), we run regressions of returns of a cryptocurrency against the returns of an equity index and indicator variables of extreme low equity index returns. For comparison purposes, we also examine the safe-haven and hedge properties of gold, silver, palladium, platinum, and diamonds for the four equity indices.

We find that Monero, Bitcoin, Dash, Litecoin, XRP, Ethereum, and NEM exhibit safe haven or hedge properties more often than rare metals and diamonds, for daily equity indices analysed, consistent with Dyhrberg (2016a), Bouri et al. (2017b), Baur et al. (2018b), and Chan et al. (2019), among others.

We also employ canonical vine (C-vine) copulas (Bedford and Cooke, 2002; Kurowicka and Cooke, 2006; Aas et al., 2009; Czado et al., 2012) for modelling the dependence among the twelve assets. C-vine copulas have an efficient ranked design, which decomposes multivariate copulas into a sequence of bivariate copulas by assigning assets nearer to the core of the arrangement according to their level of correlation with the rest of the assets. Following Low et al. (2013), Low (2018), Sahamkhadam et al. (2018), and Sahamkhadam and Stephan (2020), we conduct an out-of-sample analysis of optimal-weighting portfolio strategies, based on C-vine copulas, using cryptocurrencies and equity indices. We show that portfolio-weighting schemes based on C-vine copulas outperform benchmark strategies. Our results are robust for different rolling-window sizes. Overall, we provide evidence that the nonlinear dependence between the cryptocurrencies and the equity indices entails forward-looking measures of risk that are economically significant, which outperform benchmark strategies.

Our results are useful to portfolio managers for the design of investment currency positions. The symmetric dependence dynamics between pairs of cryptocurrencies implies that investors can use portfolio-weighting schemes based on C-vine copulas to obtain higher Sharpe, Sortino, and Omega ratios or lower volatility, VaR, and maximum drawdown. The identified CoVaR spillovers between cryptocurrencies and equity markets together with portfolio-weighting schemes based on C-vine copulas imply that cryptocurrency investors must account in their risk management approaches for the effect that equity markets have on the prices of cryptocurrencies. Likewise, equity investors may consider in their hedging and risk management approaches the spillover effect of cryptocurrencies on equity markets.

The remainder of the paper advances as follows. Section 2 revises the relevant literature. Section 3 explains the methodology implemented in the paper. Section 4 presents the data and its descriptive statistics. Section 5 discusses the empirical results. Finally, Section 6 outlines some concluding remarks.

2. Review of the literature

Understanding the price dynamics and role of *cryptocurrencies* is important for financial market investors who want to protect the value of their portfolio during market turmoil movements. For this purpose, many studies have investigated the linkage of price movements between financial assets and cryptocurrencies, usually examining the safe-haven and hedging features of cryptocurrencies. For example, Dyhrberg (2016b) found that Bitcoin is regarded as an asset between gold (with store-of-value properties) and the US dollar (as a medium-of-exchange) in portfolio management. Bouri et al. (2017a) showed that Bitcoin reacts positively to uncertainty, indicating that it acts as a hedge asset against uncertainty. Baur et al. (2018a) reported that correlation, volatility, and Bitcoin return characteristics differ from those of the US dollar and gold. Corbet et al. (2018) documented that cryptocurrencies provide diversification benefits in short-horizon investments.

Giudici and Abu-Hashish (2019) found low correlations between traditional assets (gold, oil, S&P 500, USD-Yuan FX rate, and USD-Euro FX rate) and Bitcoin. Kang et al. (2019) reported high co-movement between prices of Bitcoin and gold futures. Baumöhl (2019) documented asymmetric return connectedness between forex and cryptocurrencies by employing a quantile cross-spectral approach. Mensi et al. (2019) showed that volatility linkages between the prices of precious metals and Bitcoin are asymmetric by using high-frequency data. Selmi et al. (2018) demonstrated that both Bitcoin and gold exhibit diversifier, hedging, safe-haven features for oil price changes.

Certain studies analysed the relationship between cryptocurrency and equity markets. Brière et al. (2015) showed that the inclusion of Bitcoins improves the performance of well-diversified portfolios, implying that Bitcoin investments provide significant diversification benefits. Eisl et al. (2015) explored the impact of Bitcoin price movement on portfolio diversification by employing a conditional Value-at-Risk (CoVaR) framework, and they provided evidence that the inclusion of Bitcoin in the portfolios may enhance their performance. Dyhrberg (2016a) found that Bitcoin clearly serves as a hedge asset against the UK stock market. Bitcoin possesses hedging capabilities similar to gold, and it can hedge stock market risk. Bouoiyour and Selmi (2017) reported negative correlations between two cryptocurrencies (Bitcoin and Ether) and other assets (US stocks, US bonds, and crude oil), indicating that cryptocurrencies can hedge against the price movements of these assets. They also found that both cryptocurrencies have safe-haven properties. Bouri et al. (2017b) investigated whether Bitcoin can act as a safe haven and hedge for other assets using daily and weekly data. They found that the hedging and safe-haven characteristics of Bitcoin vary by investment horizon, and they are more suitable for diversification than for hedging. Anyfantaki et al. (2019) investigated whether risk-averse investors can obtain diversification benefits from cryptocurrencies by comparing the performance of optimal portfolios) with and without cryptocurrencies (Bitcoin, Ethereum, Ripple, and Litecoin). The authors showed that the cryptocurrencies yield potential diversification benefits and provide better investment opportunities to investors. Baur et al. (2018b) documented that Bitcoin is uncorrelated with traditional assets either during normal times or during periods of financial turmoil, and it can hedge and serve as a safe-haven asset.

Certain studies showed that Bitcoin can act as an effective hedge against stock indices. Recently, Al-Yahyaee et al. (2019) reported that gold and Bitcoin display hedging and diversification attributes for stock and oil portfolios. Chan et al. (2019) provided evidence that Bitcoin is a strong hedge for the monthly S&P 500, Euro STOXX, Shanghai A-Share, Nikkei, and TSX indices; however, the authors fail to find evidence of hedging properties of Bitcoin under daily or weekly frequency. Guesmi et al. (2019) reported that hedging strategies involving Bitcoin considerably reduce the risk of a portfolio. Kajtazi and Moro (2019) showed that the portfolio performance improves by adding Bitcoin to diversified portfolios composed of Chinese, US, and European financial assets. Kliber et al. (2019) examined whether Bitcoin acts as a safe haven, hedge, or diversifier for stock markets (Japan, China, Sweden, Venezuela, and Estonia) by estimating the dynamic conditional correlation between the two markets. They demonstrated that Bitcoin can act as a safe haven in Venezuela, and it serves as a weak hedge in Sweden and Estonia. Bouri et al. (2020a) showed that Bitcoin, Stellar, and Ripple are safe havens for US equities by employing a cross-quantilogram approach. Bouri et al. (2020b) also found that cryptocurrencies provide diversification benefits for Asian Pacific and Japanese market investors. Platanakis and Urquhart (2020) provided evidence that portfolio investors may obtain substantially higher returns by including Bitcoin in their portfolio.

Shahzad et al. (2019) provided evidence that Bitcoin can act as a weak safe haven, but its role is time varying. Stensås et al. (2019) and Shahzad et al. (2020) reported that Bitcoin acts as a hedge and as a diversifier in certain developed countries. Symitsi and Chalvatzis (2019) investigated portfolios composed of currencies, oil, gold, and stocks. They found significant diversification benefits of Bitcoin. Tiwari et al. (2020) showed that cryptocurrencies can hedge against US stock fluctuations, whereas Charfeddine et al. (2020) documented that Bitcoin and Ethereum can act as diversifiers in the US stock market. Therefore, the results of the previous literature support the idea that these cryptocurrencies can be suitable for financial diversification.

Nevertheless, Klein et al. (2018) showed that S&P 500 stock returns and Bitcoin are positively correlated during market downturns, indicating that Bitcoin acts in the exact opposite direction as gold. Bitcoin is also not considered as a safe haven or a hedging asset for equity markets in developed countries. Smales (2019) documented that Bitcoin is costlier to transact, less liquid, and more volatile than other assets, even when markets are behaving normally. Overall, empirical analyses on the role of cryptocurrencies in investment do not reach a consensus.

Our study differs from the previous studies in the analysis setting as follows. First, we analyse the most important cryptocurrencies rather than focusing on only one or two cryptocurrencies (usually Bitcoin). In addition, we include global and regional equity markets in the analysis rather than focusing only on a specific equity market. Further, we employ copulas with time-varying parameters and a CoVaR method to consider the nonlinear dependence dynamics and spillovers between cryptocurrency and equity markets. We also verify the safe-haven and hedge properties of the eight cryptocurrencies with respect to each equity index, and we compare them with the safe-haven and hedge properties of gold, silver, palladium, platinum, and diamonds for the four equity indices. Finally, we conduct an out-of-sample analysis of optimal-weighting portfolio based on C-vine copulas using cryptocurrencies and equity indices.

3. Methodology

3.1. Marginal model

To compute the marginal return distributions corresponding to cryptocurrencies and the world equity markets, we fit an ARMA structure with threshold generalized autoregressive conditional heteroskedasticity, namely, ARMA (p,q)-TGARCH(1,1). This model captures the fat tails, conditional heteroscedasticity, and leverage effects features of cryptocurrencies and world equity' returns as follows:

$$r_t = \phi_0 + \sum_{j=1}^{p} \phi_j r_{t-j} + \sum_{i=1}^{q} \Theta_i \varepsilon_{t-i}, \tag{1}$$

where ϕ_0, ϕ_j, and Θ_i are the constant, autoregressive, and moving-average parameters, respectively, and $\varepsilon_t = \sigma_t z_t$, where the conditional variance is σ_t^2 given in a TGARCH(1,1) model as:

$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \lambda \varepsilon_{t-1}^2 1(\varepsilon_{t-1} < 0), \tag{2}$$

where ω is a constant, $\alpha_1$and β_1 are the ARCH and GARCH components, respectively, λ captures the leverage effect, and $1(\cdot)$ is an indicator function that takes 1 if $\varepsilon_{t-1} < 0$ and 0 otherwise. The conditional variance proportionally increases more after a negative shock than following a positive shock of the same size when $\lambda < 0$. We assume that z_t is an i.i.d. random variable with zero mean and unit variance that follows a Hansen (1994)'s density distribution, namely the skewed-t distribution expressed as follows:

$$f(z_t|v,\eta) = \begin{cases} bc\left(1+\frac{1}{v-2}\left(\frac{bz_t+a}{1-\eta}\right)^2\right)^{-(v+1)/2} & \text{if } z_t < -a\Big/b, \\ bc\left(1+\frac{1}{v-2}\left(\frac{bz_t+a}{1+\eta}\right)^2\right)^{-(v+1)/2} & \text{if } z_t \geq -a\Big/b, \end{cases} \tag{3}$$

where v and η are the degrees of freedom and symmetry parameters, respectively, with $2 < \nu < \infty$ and $-1 < \eta < 1$. The coefficients a, b, and c are constants such that $a = 4\eta c[(v-2)/(v-1)]$, $b = 1 + 3\eta^2 - a^2$, and $c = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma(v/2)}$. When $\eta = 0$ and $\nu \to \infty$, the skewed-t distribution of Eq. (3) converges to a standard normal distribution; when $\eta = 0$ and $\nu < \infty$, the skewed-t distribution becomes a symmetric Student-t distribution.

3.2. Time-varying-parameter bivariate copulas

The concept of copulas has its origin in Sklar (1959)'s theorem, which states that the following relationship holds:

$$F_{XY}(x,y) = C(u,v), \text{for all}(x,y) \in \mathbb{R}^2 \text{and}(u,v) \in (0,1), \tag{4}$$

where $F_{XY}(x,y)$, for all $(x,y) \in \mathbb{R}^2$, is a joint distribution corresponding to the marginal distribution functions $F_X(x)$ and $F_y(y)$ of the random variables X and Y. The function $C(\cdot,\cdot)$ is the copula, and it is uniquely determined for continuous marginal distributions $F_X(\cdot)$ and $F_y(\cdot)$ such that $C(u,v) = F_{XY}(F_X^{-1}(u), F_Y^{-1}(v))$, for all $(u,v) \in \mathbb{R}^2$, where $u = F_X(\cdot)$ and $v = F_Y(\cdot)$ are random variables uniformly marginally distributed on (0,1). By differentiating Eq. (4) with respect to the marginal probability density functions $f_X(\cdot)$ and $f_Y(\cdot)$, it follows that:

$$f_{XY}(x,y) = c(u,v)f_X(x)f_Y(y), \text{for all } (x,y) \in \mathbb{R}^2 \text{ and } (u,v) \in (0,1), \tag{5}$$

where $f_{XY}(\cdot,\cdot)$ is the joint probability density function of X and Y, and $c(u,v) = \partial^2 C(u,v)/\partial u \partial v$. The lower- and upper-tail dependences based on a copula measure are defined as follows:

$$\lim_{u\to 1} Pr\left[X \geq F_X^{-1}(u) | Y \geq F_Y^{-1}(u)\right] = \lim_{u\to 1}\frac{1-2u+C(u,u)}{(1-u)} = \tau^U, \tag{6}$$

$$\lim_{u\to 0} Pr\left[X \leq F_X^{-1}(u) | Y \leq F_Y^{-1}(u)\right] = \lim_{u\to 0}\frac{C(u,u)}{u} = \tau^L, \tag{7}$$

where $F_X^{-1}(\cdot)$ and $F_Y^{-1}(\cdot)$ are the inverse marginal distribution functions and τ^U, $\tau^L \in [0,1]$. If the limits of Eqs. (6)–(7) exist, thus X and Y display lower and upper tail dependence if τ^U, $\tau^L \in (0,1]$.

We fit different types of copulas with time-varying parameters. The normal and the Student-t copulas have a linear dependence parameter, ρ_t, as per evolution in an ARMA $(1,q)$ process:

$$\rho_t = \widetilde{\Lambda}\left(\psi_0 + \psi_1\rho_{t-1} + \psi_2\frac{1}{q}\sum_{j=1}^{q}\Phi^{-1}(u_{t-j}) \bullet \Phi^{-1}(v_{t-j})\right), \tag{8}$$

where $\widetilde{\Lambda}(x) = (1-e^{-x})(1+e^{-x})^{-1}$ is a modified logistic transformation that keeps the dependence parameter ρ_t within the interval (−1,1), and $\Phi^{-1}(\cdot)$ is the inverse of the normal distribution function—see Manner and Reznikova (2012) and Patton (2012) for further details. The terms ψ_0, ψ_1, and ψ_2 are autoregressive coefficients of ρ_t. The Student-t copula function with time-varying parameter features is estimated by substituting a standard normal quantile function $\Phi^{-1}(\cdot)$ by $t_v^{-1}(\cdot)$, the inverse of the Student-t distribution with v degrees of freedom, in Eq. (8).

The tail-dependence parameters of the time-varying-parameter Clayton and Gumbel copulas also follow an ARMA $(1,q)$ process as follows:

$$\delta_t = \Lambda^*\left(\omega + \beta\delta_{t-1} + \alpha\frac{1}{q}\sum\nolimits_{j=1}^{q}|u_{t-j} - v_{t-j}|\right), \tag{9}$$

where $\Lambda^*(x) = x^2$ for the Clayton copula, which ensures that $\delta_t \in [0,\infty)$, and $\Lambda^*(x) = 1 + x^2$ for the Gumbel copula, which guarantees that $\delta_t \in [1,\infty)$. The rotated Clayton and Gumbel copulas have the same evolution of the dependence parameters as the Clayton and Gumbel copulas, respectively. Finally, we estimate the symmetrized Joe-Clayton (SJC) copula's tail dependence parameters as follows:

$$\tau_t^U = \Lambda\left(\omega_U + \beta_U\rho_{t-1} + \alpha_U\frac{1}{q}\sum\nolimits_{j=1}^{q}|u_{t-j} - v_{t-j}|\right), \tag{10}$$

$$\tau_t^L = \Lambda\left(\omega_L + \beta_L\rho_{t-1} + \alpha_L\frac{1}{q}\sum_{j=1}^{q}|u_{t-j} - v_{t-j}|\right), \tag{11}$$

where $\Lambda(x) = (1 + e^{-x})^{-1}$ indicates the logistic transformation that retains τ_t^U and τ_t^L within the interval $(0,1)$. Following Patton (2006), we set $q = 10$ for the evolution of the dependence parameters in Eqs. (8)–(11) so that all copula specifications are comparable.

3.3. Downside and upside VaR and CoVaR

The value-at-risk (VaR) measures investors' maximum losses according to a confidence level and a specific time horizon by holding a short position (i.e., upside risk) or a long position (i.e., downside risk). The downside and the upside VaR at time t for a confidence level of $(1 - \alpha)$ are $Pr(r_t \leq VaR_{\alpha,\ t}) = \alpha$ and $Pr(r_t \geq VaR_{(1-\alpha),\ t}) = \alpha$, respectively. We can calculate the downside and upside VaR as follows:

$$VaR_{\alpha,t} = \mu_t + t_{\upsilon,\eta}^{-1}(\alpha)\sigma_t, \tag{12}$$

$$VaR_{(1-\alpha),t} = \mu_t + t_{\upsilon,\eta}^{-1}(1-\alpha)\sigma_t, \tag{13}$$

where σ_t and μ_t are the standard deviation and conditional mean, respectively, of the cryptocurrency return series, and $t_{\upsilon,\ \eta}^{-1}(\alpha)$ is the α-quantile of the skewed Student-t distribution of Eq. (3). The CoVaR measure is defined as the VaR of asset i conditional on asset j experiencing a large movement — see Adrian and Brunnermeier (2016) for further details. Let r_t^S be the returns of an equity index and r_t^C be the returns of a cryptocurrency. The downside CoVaR of the returns of an equity market given an extreme downward trend in the returns of a certain cryptocurrency at a confidence level of $(1 - \beta)$ or the β-quantile of the conditional distribution of r_t^S is defined as follows:

$$Pr\left(r_t^s \leq CoVaR_{\beta,t}^{S|C} | r_t^C \leq VaR_{\alpha,t}^C\right) = \beta. \tag{14}$$

Likewise, the upside CoVaR is defined as follows:

$$Pr\left(r_t^S \geq CoVaR_{\beta,t}^{S|C} | r_t^C \geq VaR_{(1-\alpha),t}^C\right) = \beta. \tag{15}$$

We can rewrite Eq. (14) as $F_{r_t^S r_t^C}(CoVaR_{\beta,t}^{S|C}, VaR_{\alpha,t}^C)/F_{r_t^C}(VaR_{\alpha,t}^C) = \beta$. Since $F_{r_t^C}(VaR_{\alpha,\ t}^C) = \alpha$, using the copula definition of Eq. (3), we can measure the systematic impact of returns of one cryptocurrency on the returns of an equity market by solving Eqs. (14) and (15) as follows:

$$C\left(F_{r_t^s}\left(CoVaR_{\beta,t}^{S|C}\right)\alpha\right) = \beta\alpha, \tag{16}$$

$$1 - F_{r_t^S}\left(CoVaR_{\beta,t}^{S|C}\right) - F_{r_t^C}\left(VaR_{(1-\alpha),t}^C\right) + C\left(F_{r_t^S}\left(CoVaR_{\beta,t}^{S|C}\right)F_{r_t^C}\left(VaR_{(1-\alpha),t}^C\right)\right) = \beta\alpha, \tag{17}$$

where $F_{r_t^S}(\cdot)$ and $F_{r_t^C}(\cdot)$ are the marginal distributions of equity index and certain cryptocurrency returns, respectively. Therefore, it suffices to estimate the marginal distribution of r_t^C and the copula between r_t^C and r_t^S to estimate $F_{r_t^S}(CoVaR_{\beta,\ t}^{S|C})$ so that we obtain the CoVaR as $F_{r_t^S}^{-1}(F_{r_t^S}(CoVaR_{\beta,t}^{S|C}))$ as in Reboredo and Ugolini (2016) and Karimalis and Nomikos (2018).

We use the Kolmogorov-Smirnov (KS) bootstrapping test of Abadie (2002) and employed by Bernal et al. (2014) to test for the downside (upside) risk spillovers as follows:

$$H_0 : CoVaR_{\beta,t}^{S|C} = VaR_{\beta,t}^S \text{ vs.} H_1 : CoVaR_{\beta,t}^{S|C} < VaR_{\beta,t}^S, \tag{18}$$

$$KS_{mn} = \sqrt{\frac{mn}{m+n}} Sup_x|F_m(x) - G_n(x)|, \tag{19}$$

where $F_m(x)$ and $G_n(x)$ are the cumulative CoVaR and VaR distribution functions, respectively, and n and m are the sizes of the two samples. The KS test statistic does not need distribution assumptions, and it compares the two cumulative distribution functions.

3.4. Safe-haven and hedge properties of cryptocurrencies

We verify the safe-haven and hedge properties of the eight cryptocurrencies with respect to each equity index. Following the approach of Baur and Lucey (2010), Baur and McDermott (2010), Ciner et al. (2013), and Dyhrberg (2016a), we regress the returns of a cryptocurrency against the returns of an equity index and indicator variables of extreme low equity index returns as follows:

$$r_{CRYPTO,t} = b_0 + b_1 r_{INDEX,t} + b_2 D\left(r_{INDEX,t} q_{1\%}\right) + b_3 D\left(r_{INDEX,t} q_{5\%}\right) + b_4 D\left(r_{INDEX,t} q_{10\%}\right) + \varepsilon_t, \tag{20}$$

$$\sigma_t^2 = \omega + \beta_1\sigma_{t-1}^2 + \alpha_1\varepsilon_{t-1}^2 + \lambda\varepsilon_{t-1}^2 1\left(\varepsilon_{t-1} < 0\right), \tag{21}$$

Table 1
Descriptive statistics of the returns of cryptocurrencies and equity indices.

Cryptocurrencies and equity index	μ	σ	K	SK
Monero	0.003	0.069	7.677	1.019
Bitcoin	0.002	0.039	4.918	−0.263
Dash	0.002	0.059	6.139	0.851
Litecoin	0.002	0.057	12.347	1.256
Stellar	0.003	0.081	16.122	2.063
XRP	0.003	0.074	40.439	3.046
Ethereum	0.003	0.076	66.371	−3.404
NEM	0.004	0.087	17.841	1.997
World equity	0.0002	0.007	4.290	−0.697
Americas equity	0.0003	0.008	3.637	−0.483
Europe equity	−0.0001	0.009	8.066	−0.761
Asia Pacific equity	0.0001	0.008	2.859	−0.504

Note: This table presents descriptive statistics of the daily returns of cryptocurrencies and equity indices. The sample period spans from Aug 7, 2015 to Mar 28, 2019. The abbreviations μ, σ, K, and SK stand for the mean, standard deviation, kurtosis, and skewness, respectively. World equity has the code dMIWD00000PUS. Americas equity has the code MIAM00000PUS. Europe equity has the code MIER00000PUS. Asia Pacific equity has the code MIAPJ0000PUS.

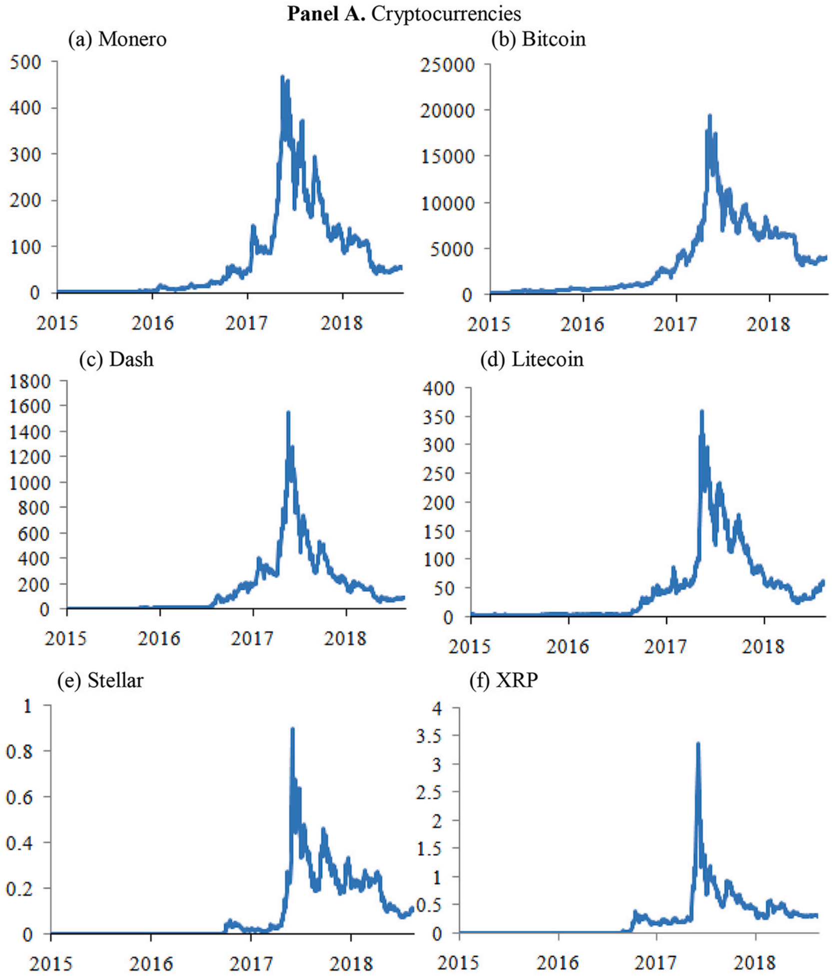


Fig. 1. Price dynamics of cryptocurrencies and equity indices.

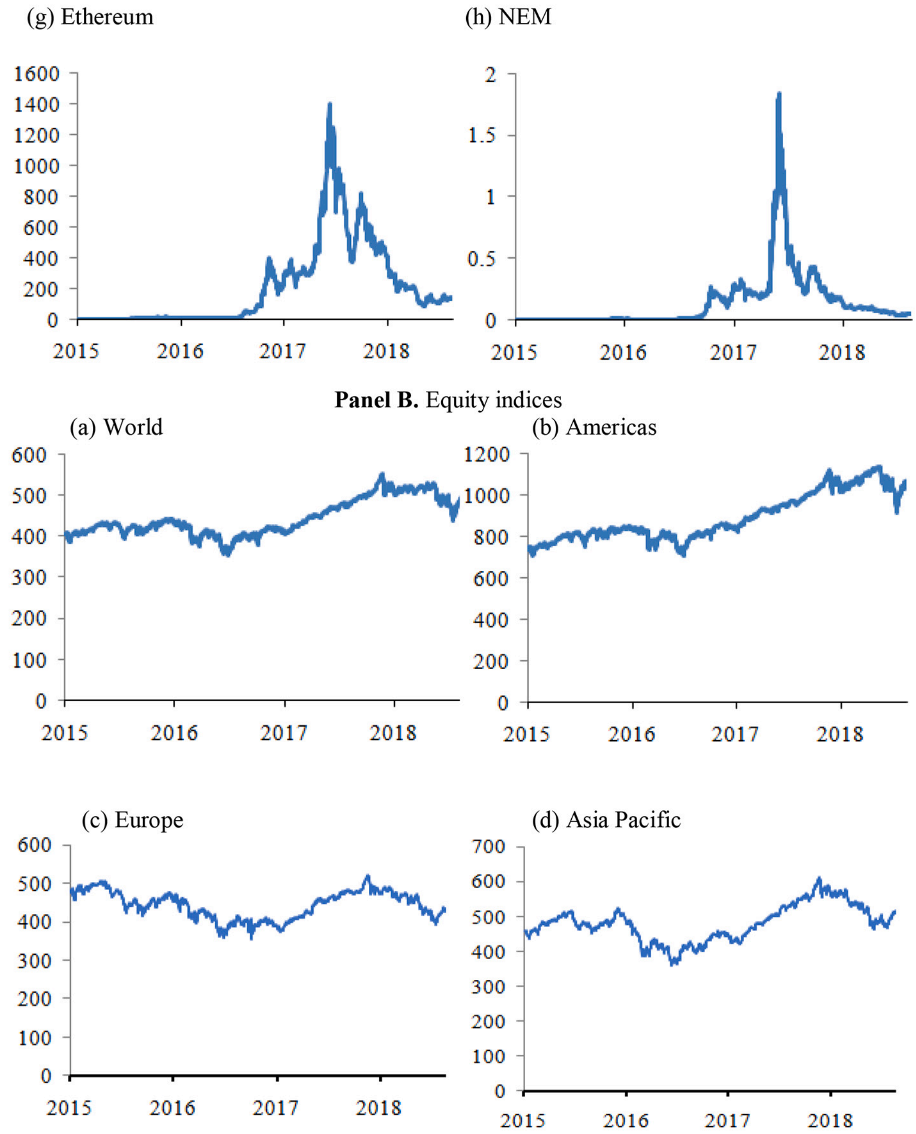


Fig. 1. (*continued*).

where $q_{1\%}$, $q_{5\%}$, and $q_{10\%}$ are the 1%, 5%, and 10% quantiles of the equity index return distribution at time t, respectively, and $D(\cdot)$ is an indicator function that takes 1 if the equity index return at time t – $r_{INDEX,\,t}$ – is lower than its q% quantile and 0 otherwise. The error term ε_t follows a T-GARCH(1,1) process with $\varepsilon_t = \sigma_t z_t$, σ_t^2 is the conditional variance, and z_t is an i.i.d. random variable with zero mean and unit variance that follows a skewed-t distribution described in Eq. (4).

Following Baur and Lucey (2010), Baur and McDermott (2010), Ciner et al. (2013), and Lucey and Li (2015), among others, we also examine the safe-haven and hedge properties of gold, silver, palladium, and platinum for the four equity indices. In addition, we also investigate the safe-haven and hedge properties of diamonds for all equity indices, in line with Auer and Schuhmacher (2013), Low et al. (2016b), and Barbi et al. (2020). Therefore, we can generalize the model of Eqs. (20)–(21) as follows:

$$r_{ASSET,t} = b_0 + b_1 r_{INDEX,t} + \sum\nolimits_{i=1}^{3} b_2(q_i) D\left(r_{INDEX,t} q_i\right) + \varepsilon_t, \tag{22}$$

where $r_{ASSET,t}$ are returns of cryptocurrencies, rare metals, and diamonds, and $\{q_1, q_2, q_3\} = \{q_{1\%}, q_{5\%}, q_{10\%}\}$ are the 1%, 5%, and 10% quantiles of the equity index return distribution at time t. The error term ε_t follows a T-GARCH(1,1) process described in Eq. (21).

If $b_1 \leq 0$ and all $b_2(q_i) \leq 0$, then the asset serves as a safe haven for the equity index. Further, if all estimated coefficients are negative and statistically significant, then the asset acts as a strong safe haven for the equity index. Finally, the asset is a hedge for the equity index if $b_1 = 0$ (weak hedge) or $b_1 < 0$ (strong hedge) and $\sum_{i=1}^{3} b_2(q_i) + b_1 \leq 0$ in case any estimated $b_2(q_i) > 0$.

Following Baur and McDermott (2010) and Low et al. (2016b), we also estimate another regression model in which the uncertainty

Table 2
Estimation results of time-varying parameter copulas.

	Monero – Bitcoin	Dash – Litecoin	Stellar – XRP	Ethereum – NEM
1. TVP-Gaussian				
ψ_0	0.167***	0.105***	0.011***	0.000
ψ_1	−0.285***	0.481***	0.316***	0.144***
ψ_2	−1.266***	1.622***	2.031***	2.067***
AIC	−3.409	−448.619	−600.045	−332.721
2. TVP-Clayton				
ω	0.182***	1.326***	0.927***	1.902***
α	−1.417***	0.178***	0.296***	0.024***
β	0.199***	−2.584***	−1.035***	−4.549***
AIC	−1.655	−528.352	−623.236	−495.065
3. TVP-Rotated Clayton				
ω	−0.236***	1.388***	0.933***	1.798***
α	−1.379***	0.190***	0.301***	−0.010***
β	1.627***	−3.531***	−1.323***	−5.005***
AIC	**−3.598**	−349.721	−447.162	−241.827
4. TVP-Gumbel				
ω	1.510***	0.892***	0.437***	0.662***
α	−1.586***	0.240***	0.355***	0.314***
β	0.880***	−2.772***	−1.161***	−2.283***
AIC	−3.238	−475.855	−592.658	−369.133
5. TVP-Rotated Gumbel				
ω	2.023***	0.813***	0.408***	1.513***
α	−1.969***	0.247***	0.363***	0.034***
β	0.323***	−2.221***	−0.947***	−3.966***
AIC	−0.617	−580.216	−688.532	−520.738
6. TVP-SJC				
ω_U	−17.635	3.475***	−1.453***	−0.229***
α_U	−2.039	−25.000***	−2.613***	−21.880***
β_U	−0.008	−1.371***	3.573***	4.412***
ω_L	−16.861***	−1.952***	−1.952***	−1.767***
α_L	−1.437	−0.594***	−0.498***	−1.029***
β_L	−0.005	4.121***	4.094***	3.965***
AIC	−0.566	**−590.025**	**−747.468**	−504.919
7. TVP-Student-*t*				
ψ_0	0.109***	0.010***	−0.046***	−0.046***
ψ_1	−0.172***	0.168***	0.124***	0.124***
ψ_2	−0.700***	1.998***	2.214***	2.214***
ν	5.000***	4.549***	4.136***	4.136***
AIC	26.532	−502.951	−672.994	**−672.994**

Note: The table displays the fit of multiple copulas with time-varying parameters. We employ the Akaike information criterion (AIC) to identify the copula that best fits the data. The table displays the results for some pairs only due to the number of calculations that is very large for all pairs. The results for other pairs are available upon request. The notation ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

of the equity index markets determines the asset-equity index relation. We use the conditional volatility of the equity index returns, estimated by a T-GARCH(1,1) process as described in Eq. (21), as an uncertainty measure as follows:

$$r_{ASSET,t} = b_0 + b_1 r_{INDEX,t} + b_2(90\%)D\left(\sigma_{INDEX,t-1} q_{90\%,t-1}\right) + b_2(95\%)D\left(\sigma_{INDEX,t-1} q_{95\%,t-1}\right) + b_2(99\%)D\left(\sigma_{INDEX,t-1} q_{99\%,t-1}\right) + \varepsilon_t, \tag{23}$$

where $q_{90\%,t-1}$, $q_{95\%,t-1}$, and $q_{99\%,t-1}$ are the 90%, 95%, and 99% quantiles of the lagged conditional volatility of the equity index returns $\sigma_{INDEX,\ t-1}$, respectively, and $D(\cdot)$ is an indicator function that takes 1 if $\sigma_{INDEX,\ t-1}$ is greater than its q% quantile at $t-1$ and 0 otherwise.

3.5. Out-of-sample analysis of optimal-weighting strategies

We perform an out-of-sample portfolio analysis of the eight cryptocurrencies and the four equity indices using different weighting

Table 3
VaR and CoVaR spillovers: World equity index.

	Downside			Upside		
	VaR	CoVaR	K-S	VaR	CoVaR	K-S
Panel A. From cryptocurrencies to the world equity index						
Monero	−0.0103	−0.0065	0.0000	0.0097	0.0118	0.2325***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Bitcoin	−0.0103	−0.0064	0.0000	0.0097	0.0108	0.1189***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Dash	−0.0103	−0.0064	0.0000	0.0097	0.0108	0.1204***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Litecoin	−0.0103	−0.0064	0.0000	0.0097	0.0107	0.1257***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Stellar	−0.0103	−0.0065	0.0000	0.0097	0.0116	0.2039***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
XRP	−0.0103	−0.0064	0.0000	0.0097	0.0111	0.1753***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Ethereum	−0.0103	−0.0066	0.0000	0.0097	0.0144	0.3860***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
NEM	−0.0103	−0.0067	0.0000	0.0097	0.0124	0.2859***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Panel B. From world equity index to cryptocurrencies						
Monero	−0.0949	−0.1053	0.1084***	0.1064	0.0883	0.0000
	(0.0011)	(0.0012)	[0.0000]	(0.0011)	(0.0009)	[1.0000]
Bitcoin	−0.0560	−0.0481	0.0000	0.0559	0.0439	0.0000
	(0.0009)	(0.0008)	[1.0000]	(0.0008)	(0.0007)	[1.0000]
Dash	−0.0797	−0.0749	0.0000	0.0908	0.0788	0.0000
	(0.0008)	(0.0008)	[0.9992]	(0.0009)	(0.0008)	[1.0000]
Litecoin	−0.0717	−0.0696	0.0090	0.0790	0.0599	0.0000
	(0.0013)	(0.0013)	[0.8964]	(0.0014)	(0.0011)	[1.0000]
Stellar	−0.1009	−0.1131	0.0798***	0.1121	0.0932	0.0000
	(0.0018)	(0.0022)	[0.0000]	(0.0019)	(0.0018)	[0.9992]
XRP	−0.0843	−0.0804	0.0030	0.0868	0.0777	0.0015
	(0.0019)	(0.0019)	[0.9879]	(0.0020)	(0.0018)	[0.9970]
Ethereum	−0.0916	−0.0979	0.0767***	0.1051	0.1249	0.1588***
	(0.0011)	(0.0012)	[0.0000]	(0.0013)	(0.0018)	[0.0000]
NEM	−0.1123	−0.1491	0.2904***	0.1236	0.1107	0.0000
	(0.0014)	(0.0019)	[0.0000]	(0.0014)	(0.0013)	[1.0000]

Note: The table shows the magnitude of the spillovers. Values in parentheses are standard errors. Values in brackets are the *p*-values of the Kolmogorov-Smirnov (K-S) test of Eq. (19), which tests $H_0 : CoVaR_{\beta,t}^{S|C} = VaR_{\beta,t}^{S}$ against $H_1 : CoVaR_{\beta,t}^{S|C} < VaR_{\beta,t}^{S}$. The notation ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

schemes. We evaluate whether the nonlinear dependence between the cryptocurrencies and the equity indices provides forward-looking measures of risk that are economically significant. Following Bedford and Cooke (2002) and Aas et al. (2009), we decompose the joint distribution of the twelve assets into many pairwise-copula densities by using a graphical representation for modelling the dependence called regular vine (R-vine), canonical vine (C-vine), and drawable vine (D-vine).

We employ C-vine copulas for modelling the dependence among the twelve assets since C-vine copulas have an efficient ranked design, which decomposes multivariate copulas into a sequence of bivariate copulas by assigning assets nearer to the core of the arrangement according to their level of correlation with the rest of the assets. By generalizing Eq. (5) for N assets, we have that

$$f(x_1, x_2, \ldots, x_N) \equiv \frac{\partial^N}{\partial x_1 \ldots \partial x_N} F(x_1, x_2, \ldots, x_N) = c(u_1, u_2, \ldots, u_N) \prod_{i=1}^{N} f_i(x_i),$$

where $f_i(x_i)$ and $c(u_1, u_2, \ldots, u_N)$ are the marginal density distribution and the copula density function, respectively, for all $(x_1, x_2, \ldots, x_N) \in \mathbb{R}^N$ and $(u_1, u_2, \ldots, u_N) \in (0,1)$. In addition, we can write the joint density function as follows:

$$f(x_1, x_2, \ldots, x_N) = f_1(x_1) f_{2|1}(x_2|x_1) f_{3|1,2}(x_3|x_1, x_2) \ldots f_{N|1,\ldots,N-1}(x_N|x_1, \ldots, x_{N-1}). \tag{24}$$

We can apply conditional copulas to decompose additionally the right-hand side of Eq. (24). By Sklar (1959)'s theorem of Eq. (5), it follows that $f_{2|1}(x_2|x_1) = c_{1,2}(F_1(x_1), F_2(x_2)) f_2(x_2)$, where$c_{1,\ 2}(F_1(x_1), F_2(x_2)) = \partial^2 C_{12}(u_1, u_2)/\partial u_1 \partial u_2$, $u_1 = F_1(x_1)$, and $u_2 = F_2(x_2)$. For instance, we may represent the joint density function of three random variables as follows:

$$f(x_1, x_2, x_3) = f_1(x_1) f_2(x_2) f_3(x_3) c_{1,2}(F_1(x_1), F_2(x_2)) c_{2,3|1}(F_{2|1}(x_2|x_1), F_{3|1}(x_3|x_1)) c_{1,3}(F_1(x_1), F_3(x_3)).$$

Following Bedford and Cooke (2002), Kurowicka and Cooke (2006), Aas et al. (2009), and Czado et al. (2012), we apply the canonical (C-vine) pair copula construction (PCC) that organizes the $N(N-1)/2$ pair-copulas of a N-dimensional PCC in $N-1$ nested trees T_n, $n = 1, \ldots, N-1$, such that each T_n has $N+1-n$ nodes and $d-n$ edges. Given a root node, the C-vine PCC models all bivariate

Table 4
VaR and CoVaR spillovers: Americas equity index.

	Downside			Upside		
	VaR	CoVaR	K-S	VaR	CoVaR	K-S
Panel A. From cryptocurrencies to the Americas equity index						
Monero	−0.0124	−0.0077	0.0000	0.0115	0.0141	0.1934***
	(0.0002)	(0.0001)	[1.0000]	(0.0002)	(0.0002)	[0.0000]
Bitcoin	−0.0124	−0.0078	0.0000	0.0115	0.0145	0.2318***
	(0.0002)	(0.0001)	[1.0000]	(0.0002)	(0.0002)	[0.0000]
Dash	−0.0124	−0.0076	0.0000	0.0115	0.0129	0.1272***
	(0.0002)	(0.0001)	[1.0000]	(0.0002)	(0.0002)	[0.0000]
Litecoin	−0.0124	−0.0078	0.0000	0.0115	0.0145	0.2318***
	(0.0002)	(0.0001)	[1.0000]	(0.0002)	(0.0002)	[0.0000]
Stellar	−0.0124	−0.0079	0.0000	0.0115	0.0150	0.2611***
	(0.0002)	(0.0001)	[1.0000]	(0.0002)	(0.0002)	[0.0000]
XRP	−0.0124	−0.0076	0.0000	0.0115	0.0132	0.1422***
	(0.0002)	(0.0001)	[1.0000]	(0.0002)	(0.0002)	[0.0000]
Ethereum	−0.0124	−0.0078	0.0000	0.0115	0.0132	0.1422***
	(0.0002)	(0.0001)	[1.0000]	(0.0002)	(0.0002)	[0.0000]
NEM	−0.0124	−0.0076	0.0000	0.0115	0.0140	0.1791***
	(0.0002)	(0.0002)	[1.0000]	(0.0002)	(0.0002)	[0.0000]
Panel B. From Americas equity index to cryptocurrencies						
Monero	−0.0949	−0.1043	0.0843***	0.1064	0.0876	0.0000
	(0.0011)	(0.0013)	[0.0000]	(0.0011)	(0.0009)	[1.0000]
Bitcoin	−0.0560	−0.0564	0.0128	0.0559	0.0489	0.0000
	(0.0009)	(0.0009)	[0.8029]	(0.0008)	(0.0007)	[1.0000]
Dash	−0.0797	−0.0752	0.0000	0.0908	0.0791	0.0000
	(0.0008)	(0.0008)	[1.0000]	(0.0009)	(0.0008)	[1.0000]
Litecoin	−0.0717	−0.0816	0.0910***	0.0790	0.0669	0.0000
	(0.0013)	(0.0015)	[0.0000]	(0.0014)	(0.0011)	[1.0000]
Stellar	−0.1009	−0.1430	0.2694***	0.1121	0.0986	0.0000
	(0.0018)	(0.0022)	[0.0000]	(0.0019)	(0.0017)	[1.0000]
XRP	−0.0843	−0.0786	0.0000	0.0868	0.0759	0.0000
	(0.0019)	(0.0018)	[1.0000]	(0.0020)	(0.0017)	[1.0000]
Ethereum	−0.0916	−0.0985	0.0820***	0.1051	0.1187	0.1226***
	(0.0011)	(0.0012)	[0.0000]	(0.0013)	(0.0016)	[0.0000]
NEM	−0.1123	−0.1235	0.0828***	0.1236	0.1064	0.0038
	(0.0014)	(0.0018)	[0.0000]	(0.0014)	(0.0015)	[0.9812]

Note: The table shows the magnitude of the spillovers. Values in parentheses are standard errors. Values in brackets are the *p*-values of the Kolmogorov-Smirnov (K-S) test of Eq. (19), which tests $H_0: CoVaR_{\beta,t}^{S|C} = VaR_{\beta,t}^{S}$ against $H_1: CoVaR_{\beta,t}^{S|C} < VaR_{\beta,t}^{S}$. The notation ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

dependencies relative to this root node conditioned on all prior root nodes, which results in the C-vine decomposition of a joint density function with N dimension as follows:

$$f(x_1, x_2, \dots, x_N) = \prod_{i=1}^{N} f_i(x_i) \times \prod_{k=1}^{N-1} \prod_{j=1}^{N-k} c_{k,k+j|1:(k-1)}\left(F(x_k|x_1, \dots, x_{k-1}), F(x_{k+j}|x_1, \dots, x_{k-1}) \,|\boldsymbol{\theta}_{k,k+j|1:(k-1)}\right),$$

where $f_i(\cdot)$ are the marginal densities, $c_{k,k+j|1:(k-1)}(\cdot,\cdot\,|\boldsymbol{\theta}_{k,k+j|1:(k-1)})$ are the bivariate copula densities, and $\boldsymbol{\theta}_{k,k+j|1:(k-1)}$ is a vector of parameters in which 1: $(k-1)$ denotes 1, …, $(k-1)$. In line with Low et al. (2013), Low (2018), and Sahamkhadam and Stephan (2020), we model the C-vine PCC by assigning assets nearer to the core of the C-vine structure according to their level of correlation with the rest of the assets. We perform our analysis for rolling windows with 500 and 1000 daily returns that correspond to 829 and 329 out-of-sample periods, respectively. We use the Normal, Clayton, Gumbel, Rotated Clayton, Rotated Gumbel, and Student-*t* copulas to model the bivariate PCC, and we update the estimation of the copula parameters at every out-of-sample forecast.

Following Low et al. (2013), Low (2018), Sahamkhadam et al. (2018), and Sahamkhadam and Stephan (2020), we perform the out-of-sample analysis of the eight cryptocurrencies and the four equity indices as follows. We fit an AR(1)-TGARCH(1,1) with a skewed-*t* distribution model to forecast one-step-ahead mean and volatility of each return. Then, we apply the probability integral transform to the standardized residuals to estimate marginal uniforms. Next, we model a C-vine copula to the marginal uniforms to estimate the joint dependence, and we simulate 10,000 multivariate uniforms with the estimated dependence arrangement. Subsequently, we apply the estimated marginal distribution functions on these simulated uniform variables to estimate standardized residuals, which in turn are inserted into the estimated AR(1)-TGARCH(1,1) model to produce 10,000 one-step-ahead forecasts for each one of the returns. Finally, we use the 10,000 forecast returns in portfolio-optimization methods to obtain optimal portfolio weights. We repeat this procedure for all one-step-ahead forecasts.

Following Low et al. (2013), Low et al. (2016a), Sahamkhadam et al. (2018), Rad et al. (2020), and Sahamkhadam and Stephan (2020), we calculate portfolio weights using five different criteria: the certainty equivalent tangency (CET), the global minimum

Table 5
VaR and CoVaR spillovers: Europe equity index.

	Downside			Upside		
	VaR	CoVaR	K-S	VaR	CoVaR	K-S
Panel A. From cryptocurrencies to Europe equity index						
Monero	−0.0144	−0.0091	0.0000	0.0133	0.0146	0.1114***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0002)	[0.0000]
Bitcoin	−0.0144	−0.0093	0.0000	0.0133	0.0162	0.2453***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0002)	[0.0000]
Dash	−0.0144	−0.0091	0.0000	0.0133	0.0150	0.1685***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0002)	[0.0000]
Litecoin	−0.0144	−0.0093	0.0000	0.0133	0.0192	0.4003***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0003)	[0.0000]
Stellar	−0.0144	−0.0092	0.0000	0.0133	0.0157	0.1949***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0002)	[0.0000]
XRP	−0.0144	−0.0091	0.0000	0.0133	0.0147	0.1174***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0002)	[0.0000]
Ethereum	−0.0144	−0.0093	0.0000	0.0133	0.0186	0.3672***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0002)	[0.0000]
NEM	−0.0144	−0.0092	0.0000	0.0133	0.0154	0.1768***
	(0.0001)	(0.0002)	[1.0000]	(0.0001)	(0.0002)	[0.0000]
Panel B. From Europe equity index to cryptocurrencies						
Monero	−0.0949	−0.0946	0.0203	0.1064	0.0818	0.0000
	(0.0011)	(0.0011)	[0.5747]	(0.0011)	(0.0009)	[1.0000]
Bitcoin	−0.0560	−0.0572	0.0218	0.0559	0.0502	0.0000
	(0.0009)	(0.0009)	[0.5279]	(0.0008)	(0.0008)	[1.0000]
Dash	−0.0797	−0.0764	0.0038	0.0908	0.0803	0.0023
	(0.0008)	(0.0008)	[0.9812]	(0.0009)	(0.0009)	[0.9932]
Litecoin	−0.0717	−0.0828	0.0948***	0.0790	0.0792	0.0226
	(0.0013)	(0.0015)	[0.0000]	(0.0014)	(0.0016)	[0.5047]
Stellar	−0.1009	−0.1112	0.0963***	0.1121	0.0919	0.0000
	(0.0018)	(0.0020)	[0.0000]	(0.0019)	(0.0016)	[1.0000]
XRP	−0.0843	−0.0775	0.0015	0.0868	0.0746	0.0000
	(0.0019)	(0.0019)	[0.9970]	(0.0020)	(0.0018)	[0.9992]
Ethereum	−0.0916	−0.0972	0.0715***	0.1051	0.1170	0.0813***
	(0.0011)	(0.0012)	[0.0011]	(0.0013)	(0.0017)	[0.0000]
NEM	−0.1123	−0.1179	0.0482	0.1236	0.1027	0.0000
	(0.0014)	(0.0016)	[0.0445]	(0.0014)	(0.0013)	[1.0000]

Note: The table shows the magnitude of the spillovers. Values in parentheses are standard errors. Values in brackets are the *p*-values of the Kolmogorov-Smirnov (K-S) test of Eq. (19), which tests $H_0 : CoVaR_{\beta,t}^{S|C} = VaR_{\beta,t}^{S}$ against $H_1 : CoVaR_{\beta,t}^{S|C} < VaR_{\beta,t}^{S}$. The notation ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

variance (GMV), the minimum conditional value-at-risk (Min-CVaR), the equally-weighted (EW) portfolio, and the historical mean portfolio. Let $\boldsymbol{r}_t = (r_{1,t}, \dots, r_{12,t})'$ and $\boldsymbol{w}_t = (w_{1,t}, \dots, w_{12,t})'$ be vectors of returns and portfolio weights at time t, respectively, and let $\boldsymbol{\Sigma}$ be the 12×12-covariance matrix of $\boldsymbol{r}_t$ at time t. The CET portfolio maximizes the mean-variance ratio of the returns as suggested by Markowitz (1952). Thus, the CET portfolio weights maximize the Sharpe ratio (SR) of the portfolio as follows:

$$\max_{\boldsymbol{w}_t} \boldsymbol{w}_t^{'}\boldsymbol{r}_t \left(\boldsymbol{w}_t^{'}\boldsymbol{\Sigma}\boldsymbol{w}_t\right)^{-1/2} \text{ s.t.} \boldsymbol{w}_t^{'}\boldsymbol{1} = 1, w_{i,t} \geq 0, \forall i = 1, \dots, 12, \tag{25}$$

where $w_{i,t} \geq 0$, $\forall i = 1, \dots, 12$, implies that investors only take long positions. The GMV strategy (Merton, 1980) aims at minimizing the variance of the portfolio as follows:

$$\min_{\boldsymbol{w}_t} \boldsymbol{w}_t^{'}\boldsymbol{\Sigma}\boldsymbol{w}_t \text{ s.t.} \boldsymbol{w}_t^{'}\boldsymbol{1} = 1, w_{i,t} \geq 0, \forall i = 1, \dots, 12. \tag{26}$$

We also consider a Min-CVaR strategy that minimizes the portfolio's downside risk measured by the conditional value-at-risk (CVaR). We use the CVaR instead of the VaR as a risk measure because the former is a coherent risk measure (Artzner et al., 1999), and it calculates the size of the expected losses lower than the VaR threshold. The Min-CVaR solves the following optimization problem (Rockafellar and Uryasev, 2000, 2002):

$$\min_{\boldsymbol{w}_t, VaR_\alpha, z} VaR_\alpha + \frac{1}{M(1-\alpha)} \sum\nolimits_{j=1}^{M} z_j \tag{27}$$

$$\text{s.t.} z_j \geq -\boldsymbol{w}_t^{'}\boldsymbol{r}_t - VaR_\alpha \geq 0, \forall j = 1, \dots, \text{M},$$

$$\boldsymbol{w}_t^{'}\boldsymbol{1} = 1, w_{i,t} \geq 0, \forall i = 1, \dots, 12,$$

Table 6
VaR and CoVaR spillovers: Asia Pacific equity index.

	Downside			Upside		
	VaR	CoVaR	K-S	VaR	CoVaR	K-S
Panel A. From cryptocurrencies to Asia equity index						
Monero	−0.0132	−0.0088	0.0000	0.0120	0.0154	0.3521***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Bitcoin	−0.0132	−0.0087	0.0000	0.0120	0.0165	0.4056***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Dash	−0.0132	−0.0086	0.0000	0.0120	0.0141	0.2430***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Litecoin	−0.0132	−0.0086	0.0000	0.0120	0.0146	0.2746***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Stellar	−0.0132	−0.0088	0.0000	0.0120	0.0153	0.3326***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
XRP	−0.0132	−0.0085	0.0000	0.0120	0.0137	0.1971***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0002)	[0.0000]
Ethereum	−0.0132	−0.0087	0.0000	0.0120	0.0162	0.3943***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
NEM	−0.0132	−0.0087	0.0000	0.0120	0.0150	0.2957***
	(0.0001)	(0.0001)	[1.0000]	(0.0001)	(0.0001)	[0.0000]
Panel B. From Asia equity index to cryptocurrencies						
Monero	−0.0949	−0.1282	0.2325***	0.1064	0.0924	0.0000
	(0.0011)	(0.0019)	[0.0000]	(0.0011)	(0.0010)	[1.0000]
Bitcoin	−0.0560	−0.0595	0.0534	0.0559	0.0560	0.0135
	(0.0009)	(0.0009)	[0.0217]	(0.0008)	(0.0008)	[0.7818]
Dash	−0.0797	−0.0779	0.0023	0.0908	0.0819	0.0000
	(0.0008)	(0.0008)	[0.9932]	(0.0009)	(0.0009)	[1.0000]
Litecoin	−0.0717	−0.0786	0.0655***	0.0790	0.0654	0.0000
	(0.0013)	(0.0015)	[0.0032]	(0.0014)	(0.0012)	[1.0000]
Stellar	−0.1009	−0.1368	0.2182***	0.1121	0.0969	0.0000
	(0.0018)	(0.0033)	[0.0000]	(0.0019)	(0.0017)	[1.0000]
XRP	−0.0843	−0.0773	0.0000	0.0868	0.0744	0.0000
	(0.0019)	(0.0017)	[1.0000]	(0.0020)	(0.0016)	[1.0000]
Ethereum	−0.0916	−0.0973	0.0647***	0.1051	0.1155	0.0436
	(0.0011)	(0.0013)	[0.0036]	(0.0013)	(0.0021)	[0.0776]
NEM	−0.1123	−0.1255	0.1099***	0.1236	0.1078	0.0000
	(0.0014)	(0.0016)	[0.0000]	(0.0014)	(0.0013)	[0.9992]

Note: The table shows the magnitude of the spillovers. Values in parentheses are standard errors. Values in brackets are the *p*-values of the Kolmogorov-Smirnov (K-S) test of Eq. (19), which tests $H_0: CoVaR_{\beta,t}^{S|C} = VaR_{\beta,t}^{S}$ against $H_1: CoVaR_{\beta,t}^{S|C} < VaR_{\beta,t}^{S}$. The notation ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

where $z_j = (-\boldsymbol{w}_t'\boldsymbol{r}_t^j - VaR_\alpha)^+$ are simulated random variables using the vine copula approach, and M is the number of simulations. We also specify an EW and a historical mean portfolio as benchmark strategies. The historical mean portfolio is an EW portfolio on assets whose expected returns at the subsequent period are positive, based on the historical means of each return.

4. Data

In our analysis, we use daily frequency price series of the cryptocurrencies known as Monero, Bitcoin, Dash, Litecoin, Stellar, XRP, Ethereum, and NEM. We also use daily frequency price series of the world, America, Europe, and Asia Pacific equity indices. The data samples span from 7 August 2015 to 23 March 2019. For the modelling of dynamic dependence using time-varying parameter copulas, we use the copula data, and for the VaR and CoVaR modelling, we use logarithmic returns. Table 1 displays descriptive statistics of the series. Among the cryptocurrencies, NEM has the largest mean return and the largest volatility. The smallest mean returns correspond to Bitcoin, Dash, and Litecoin, with Bitcoin having the lowest volatility. All equity indices have zero-mean returns and the lowest volatilities among the twelve assets. Among the cryptocurrencies, Bitcoin and Ethereum are the only ones displaying negative skewness. XRP and Stellar display the largest positive skewness values, and all equity indices present negative skewness. The kurtosis values of all cryptocurrencies and equity indices are >3, indicating the absence of normality in the returns' distribution. Besides, unreported Jarque-Bera tests reject the null hypothesis of normality for each series at the 5% level.

Fig. 1 shows the dynamics of the prices of the cryptocurrencies and global and regional equity indices. All cryptocurrencies experienced a sharp increase in prices around the middle of 2017. This sharp increase in prices was followed by a sharp decrease in prices, indicating cryptocurrencies' high price volatility. The world and Americas equity indices are in a trend of escalation throughout the entire sample. Both indices experience a mild decline in the middle of 2016. The Europe and Asia Pacific equity indices do not show a long-term trend of decline or escalation. From the beginning of the sample to the middle of 2016, they undergo a mild trend of decline. Subsequently, they undergo a trend of escalation that ends around the fourth quarter of 2017. From the fourth quarter of 2017

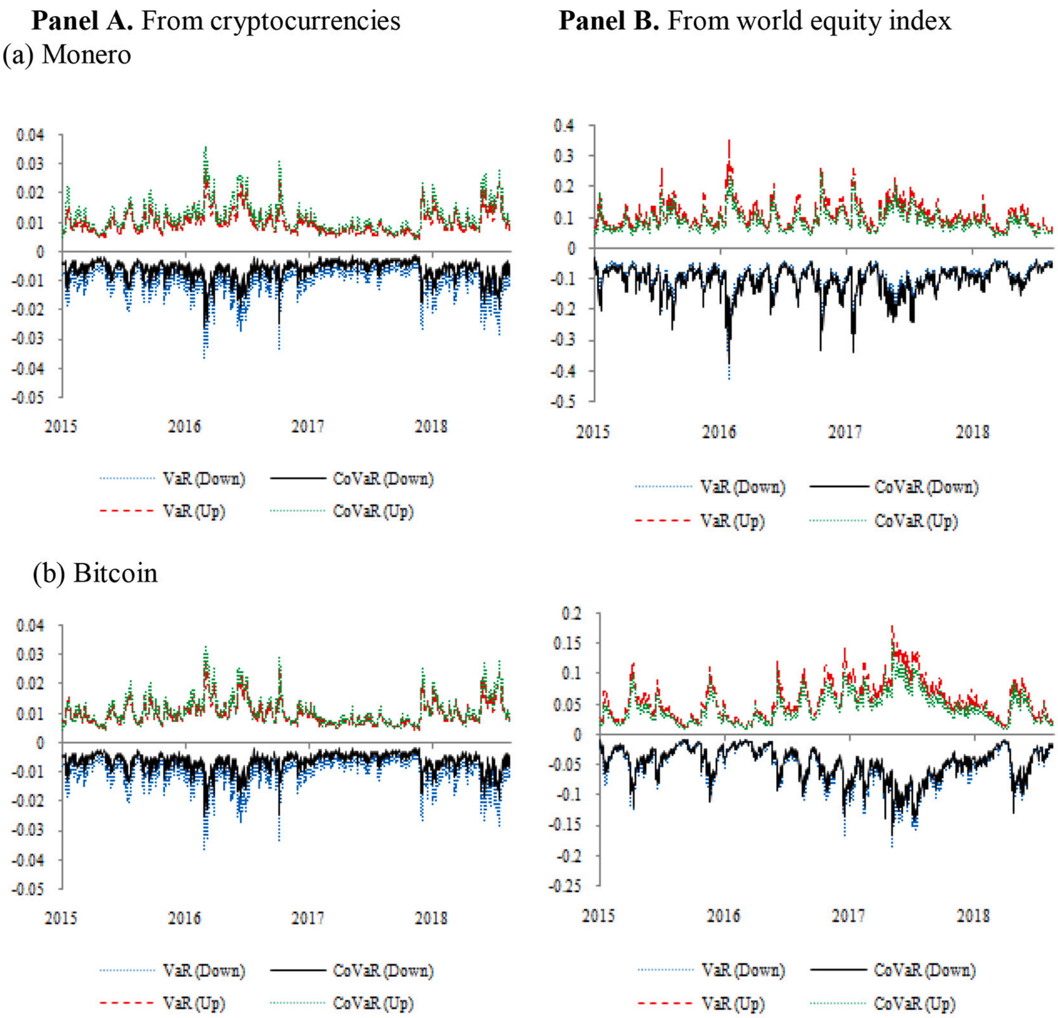


Fig. 2. Risk spillover between cryptocurrencies and world equity index.

to the end of the sample period, both equity indices experience a downward trend.

5. Empirical results

5.1. TVP bivariate copula results

To examine the dependence structure between cryptocurrencies and the world equity returns, we carry out different GARCH models with varying lag orders (from zero to four). The standardized residuals are used for time-invariant and time-varying parameter (TVP) copula estimations that are generated from the best fitted marginal model, ARMA(p, q)-TGARCH(1,1) for our study. Like the marginal model, the best copulas are those that minimize the Akaike information criterion values (with bold values in Table 2). The results show that the time-varying copula outperforms the time-invariant copula, indicating a temporal dependence between cryptocurrencies and the world equity returns. The estimation results of marginal models and static copulas are available upon request. We infer that the dependence dynamics between pairs of cryptocurrencies is symmetric or asymmetric according to the best copulas of the symmetric or asymmetric types.

Table 2 displays the results of the implemented bivariate copulas to the pairs of cryptocurrencies. The analysis of the AICs indicates that the rotated Clayton is the best one for the dependence relationship between the pair Monero-Bitcoin. Since this copula is asymmetric at the positive tail, we infer that the dependence relationship between Monero and Bitcoin tends to strengthen during market upturns. Besides, the relationship between the pairs of cryptocurrencies Dash-Litecoin and Stellar-XRP is best captured by the symmetrized Joe-Clayton copula. This finding implies that the strength of dependence between these two pairs of cryptocurrencies tends to be constant in the centre and in the tails. Finally, the dependence relationship between the pair of cryptocurrencies Ethereum-

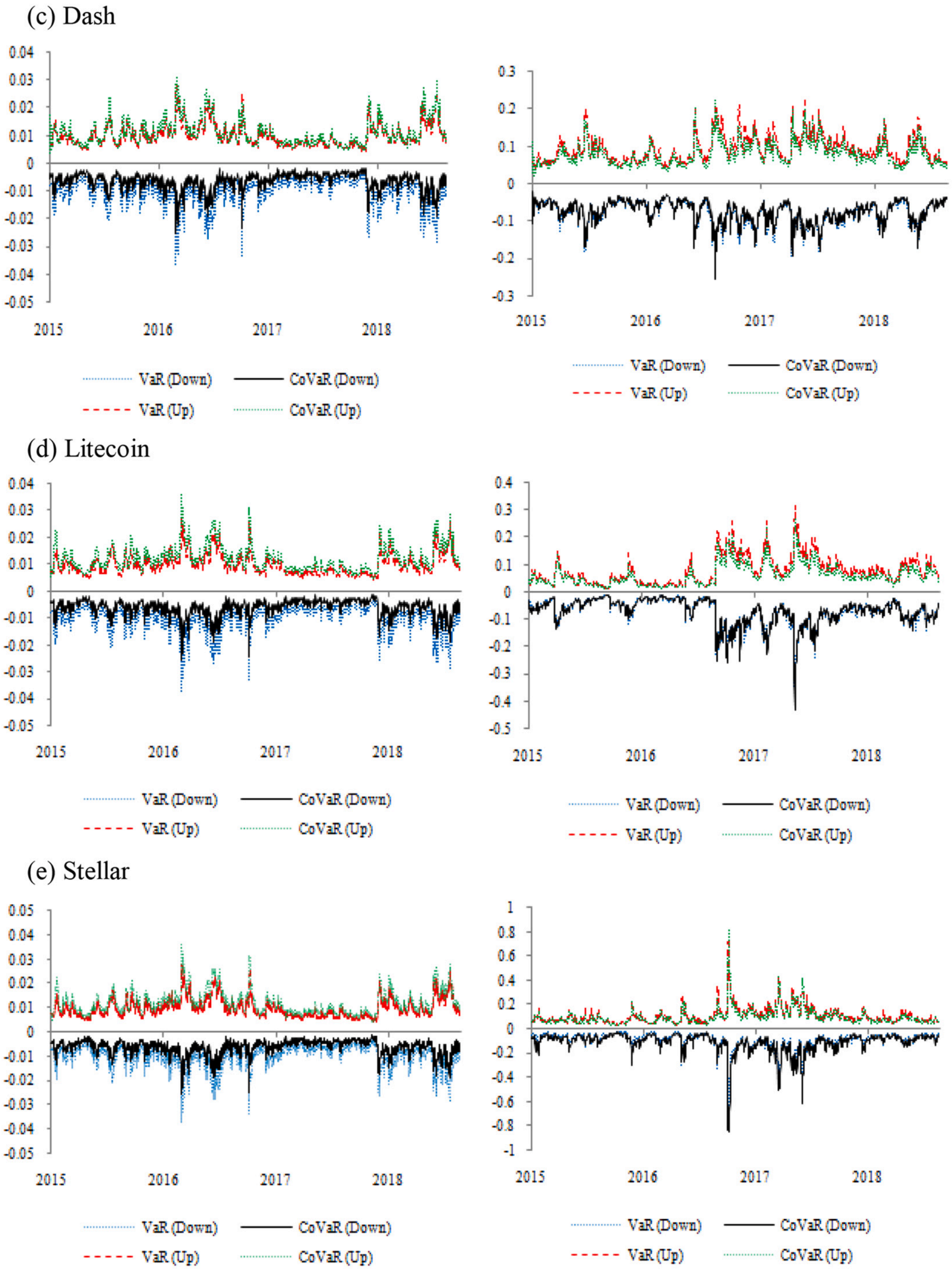


Fig. 2. (*continued*).

NEM is best accounted for by the Student-*t* copula, which is fat-tailed and symmetric across the distribution. Thus, just as for the pairs Dash-Litecoin and Stellar-XRP, the dependence relationship between Ethereum and NEM is constant in the centre and at the tails of the distribution.

A summary of the time-varying parameter copula results shows that the dependence dynamics of the portfolio of cryptocurrencies displays both symmetric and asymmetric features, with the symmetric dynamics being more predominant overall.

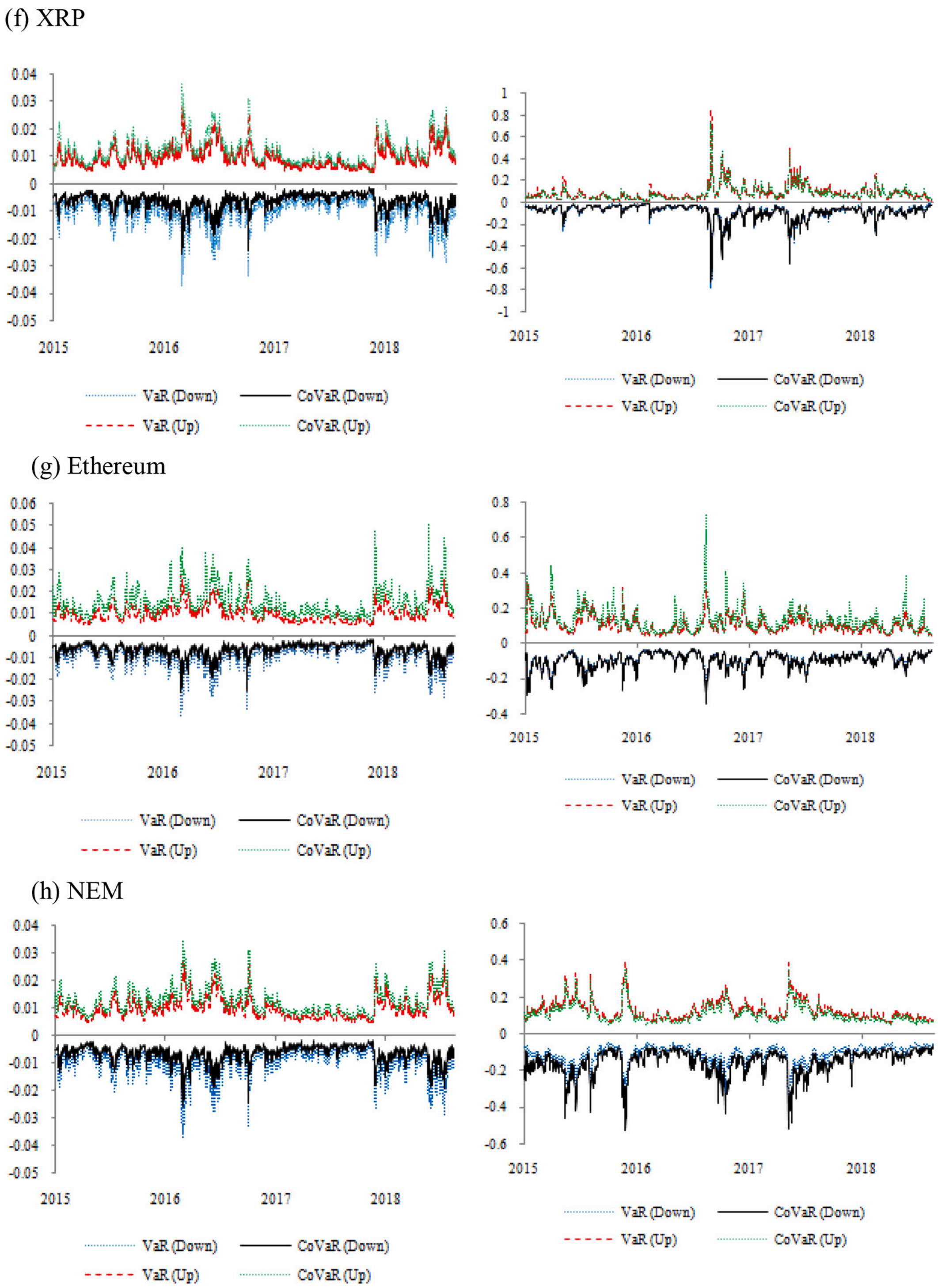


Fig. 2. (*continued*).

5.2. VaR and CoVaR results

In this subsection, we analyse the conditional Value-at-Risk (CoVaR) and Value-at-Risk (VaR) spillovers that cryptocurrencies exert on the world equity index, the Americas equity index, the Europe equity index, and the Asia Pacific equity index, and vice versa. We identify the cryptocurrencies that most largely spillover on the global and regional equity indices and vice versa.

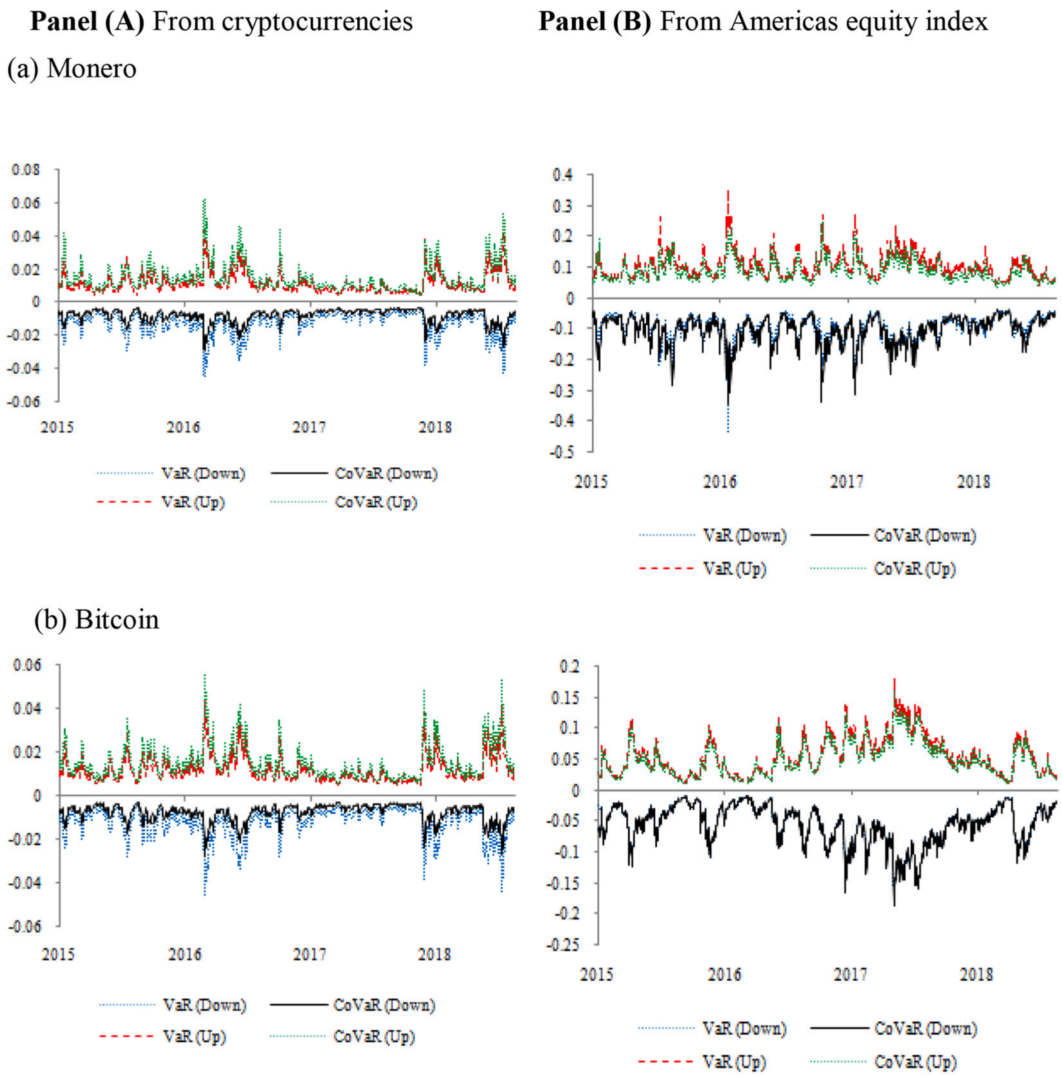


Fig. 3. Risk spillover between cryptocurrencies and Americas equity index.

Table 3 displays the CoVaR and VaR spillovers from cryptocurrencies to the world equity index and vice versa. Panel A of Table 3 indicates that the largest downside CoVaR spillovers to the world equity index are exerted by NEM (−0.0067), followed by Ethereum (−0.0066), and to a lesser degree by Monero (−0.0065) and Stellar (−0.0065). The downside VaR spillovers from all cryptocurrencies to the world equity index are similar. On the upside, the largest CoVaR spillovers to the world equity index are exerted by Ethereum (0.0144), followed by NEM (0.0124), and to a lesser degree by Stellar (0.0116).

The downside VaR and CoVaR spillovers from all cryptocurrencies to the world equity index are similar. Panel B of Table 3 illustrates that the largest downside CoVaR spillovers from the world equity index are to NEM (−0.1491), followed by Stellar (−0.1131), and to a lesser degree by Monero (−0.1053). The largest downside VaR spillovers from the world equity index are to NEM (−0.1123) and Stellar (−0.1009). On the upside, the largest CoVaR spillovers from the world equity index are to Ethereum (0.1249), followed by NEM (0.1107), and to a lesser degree by Stellar (0.0932). The largest upside VaR spillovers from the world equity index are to NEM (0.1236) and Stellar (0.1121), and to a lesser degree to Ethereum (0.1051).

Table 4 presents the CoVaR and VaR spillovers from cryptocurrencies to the Americas equity index and vice versa. Panel A of Table 4 indicates that the largest downside CoVaR spillovers to the Americas equity index are exerted by Stellar (−0.0079), followed by Bitcoin (−0.0078), Litecoin (−0.0078), and Ethereum (−0.0078). The downside VaR spillovers from all cryptocurrencies to the Americas equity index are similar. On the upside, by Stellar (0.0150), followed by Bitcoin (0.0145), and Litecoin (0.0145) exert the largest CoVaR spillovers to the Americas equity index. The upside VaR spillovers from all cryptocurrencies to the Americas equity index are similar.

Panel B of Table 4 reports that the largest downside CoVaR spillovers from the Americas equity index to the cryptocurrencies are to

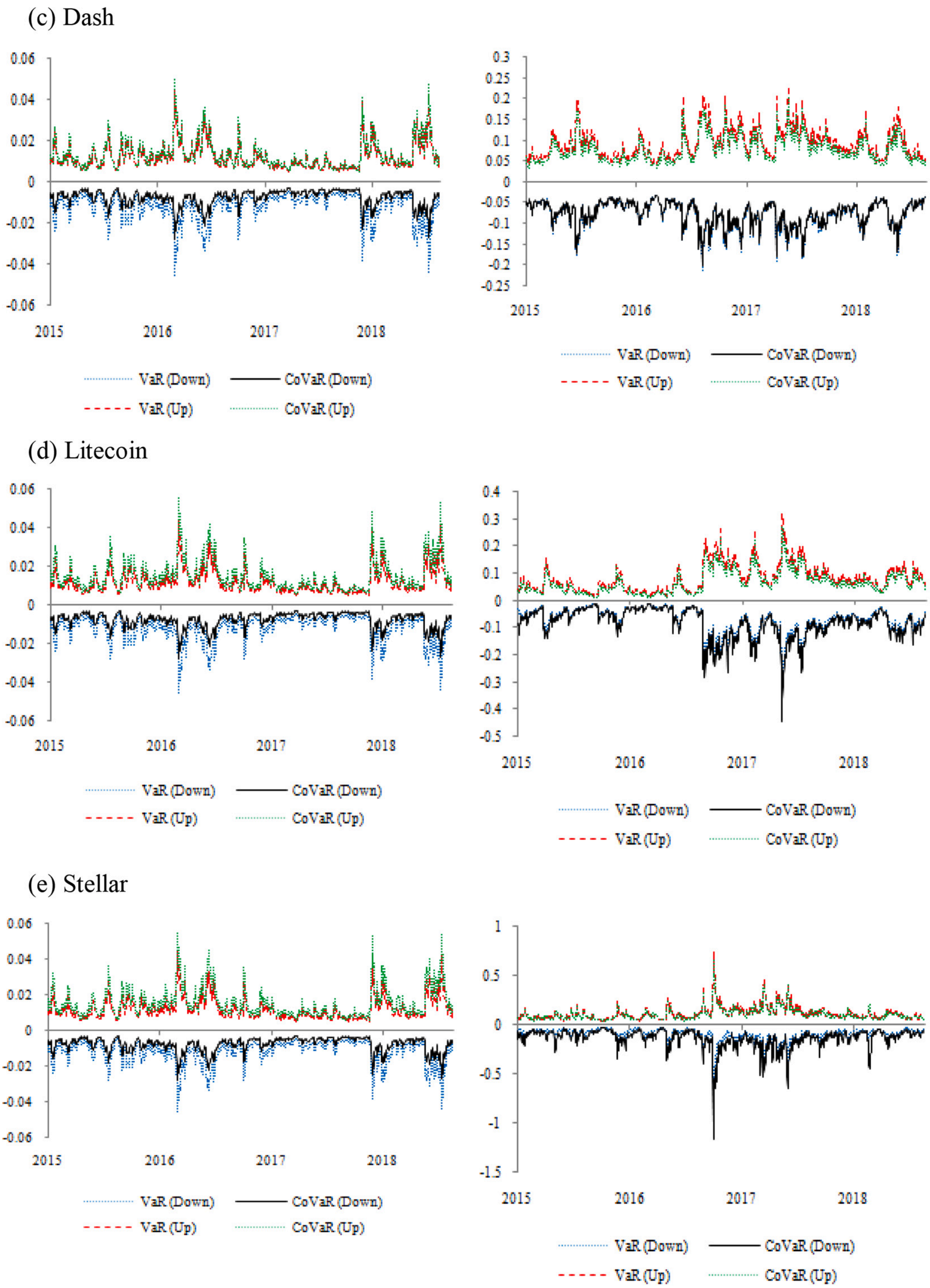


Fig. 3. (*continued*).

Stellar (−0.1430), followed by NEM (−0.1235), and to a lesser degree by Monero (−0.1043). The largest downside VaR spillovers from the Americas equity index are to NEM (−0.1123) followed by Stellar (−0.1009). On the upside, the largest CoVaR spillovers from the Americas equity index are to Ethereum (0.1187) followed by NEM (0.1064). The largest upside VaR spillovers from the Americas equity index are to NEM (0.1236), followed by Stellar (0.1121), and to a lesser degree by Monero (0.1064).

Table 5 reports the CoVaR and VaR spillovers from cryptocurrencies to the Europe equity index and vice versa. Panel A of Table 5

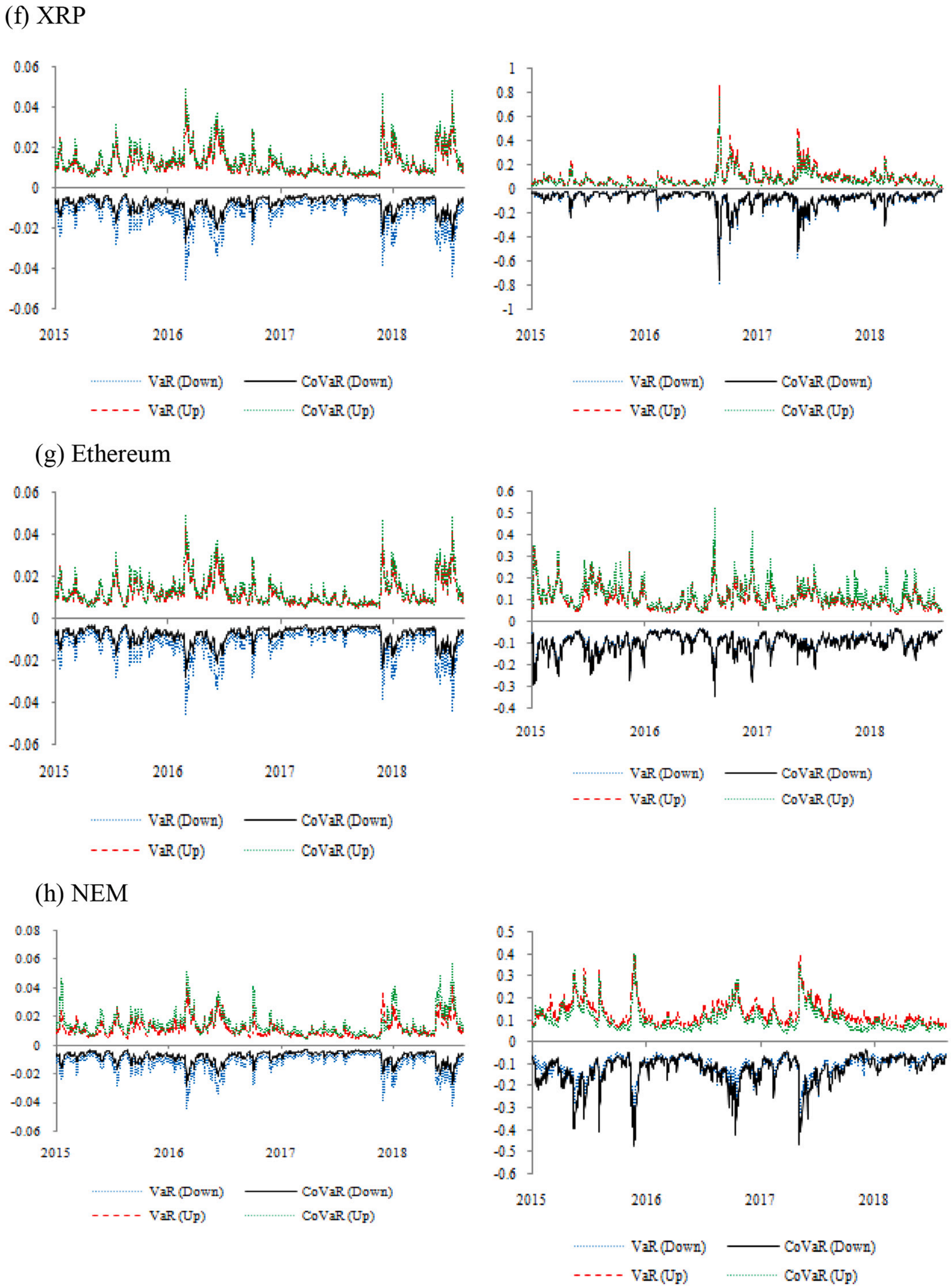


Fig. 3. (*continued*).

indicates that the largest downside CoVaR spillovers to the Europe equity index are exerted by Bitcoin (−0.0093), Litecoin (−0.0093), and Ethereum (−0.0093). The downside VaR spillovers from all cryptocurrencies to the Europe equity index are similar. On the upside, Litecoin (0.0192) and Ethereum (0.0186) exhibit the largest CoVaR spillovers to the Europe equity index. The upside VaR spillovers from all cryptocurrencies to the Europe equity index are similar.

Panel B of Table 5 demonstrates that the largest downside CoVaR spillovers from the Europe equity index are to NEM (−0.1179) followed by Stellar (−0.1112). The largest downside VaR spillovers from the Europe equity index are to NEM (−0.1123) followed by

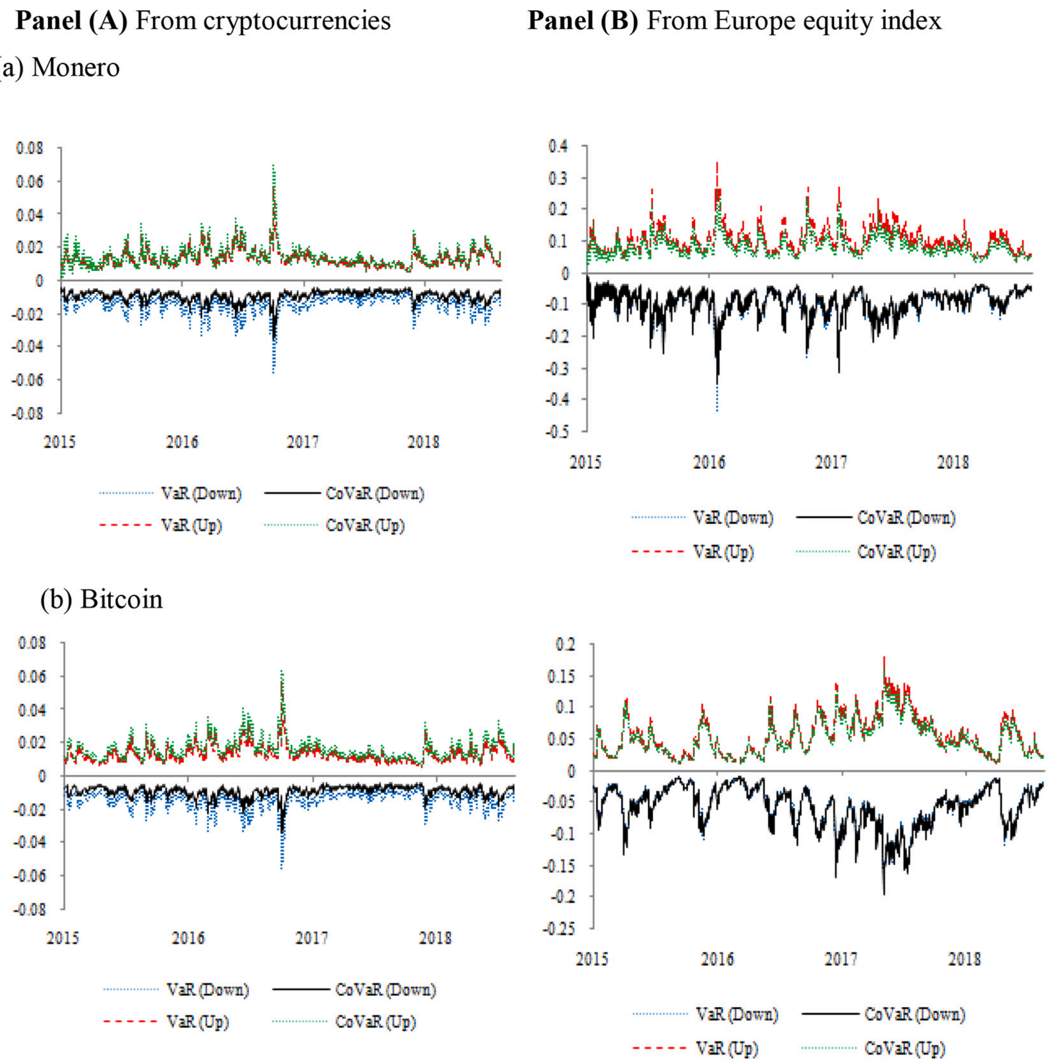


Fig. 4. Risk spillover between cryptocurrencies and Europe equity index.

Stellar (−0.1009). On the upside, the largest CoVaR spillovers from the Europe equity index are to Ethereum (0.1170) followed by NEM (0.1027). The largest upside VaR spillovers from the Europe equity index are to NEM (0.1236) followed by Stellar (0.1121).

Table 6 shows the CoVaR and VaR spillovers from cryptocurrencies to the Asia Pacific equity index and vice versa. Panel A of Table 6 illustrates that the largest downside CoVaR spillovers to the Asia Pacific equity index are exerted by Stellar (−0.0088) and Monero (−0.0088). The downside VaR spillovers from all cryptocurrencies to the Asia Pacific equity index are similar. On the upside, the largest CoVaR spillovers to the Asia Pacific equity index are exerted by Bitcoin (0.0165) followed by Ethereum (0.0162). The upside VaR spillovers from all cryptocurrencies to the Asia Pacific equity index are similar.

Panel B of Table 6 indicates that the largest downside CoVaR spillovers from the Asia Pacific equity index are to Stellar (−0.1368), followed by Monero (−0.1282), and to a lesser degree to NEM (−0.1255). The largest downside VaR spillovers from the Asia Pacific equity index are to NEM (−0.1123) followed by Stellar (−0.1009). On the upside, the largest CoVaR spillovers from the Asia Pacific equity index are to Ethereum (0.1155) followed by NEM (0.1078). The largest upside VaR spillovers from the Asia Pacific equity index are to NEM (0.1236) followed by Stellar (0.1121).

Fig. 2 plots the CoVaR and VaR spillovers from cryptocurrencies to world equity index and vice versa. Both the downside and upside spillovers largely fluctuate between 2016 and 2017, indicating that this was a volatile period. Overall, the VaR and CoVaR spillovers from cryptocurrencies to the world equity index fluctuate more than the spillovers exerted by the world equity index on the cryptocurrencies.

Fig. 3 displays the CoVaR and VaR spillovers from cryptocurrencies to the Americas equity index and vice versa. Overall, the risk spillovers on the downside are more volatile than the risk spillovers on the upside. The risk spillovers from cryptocurrencies to the

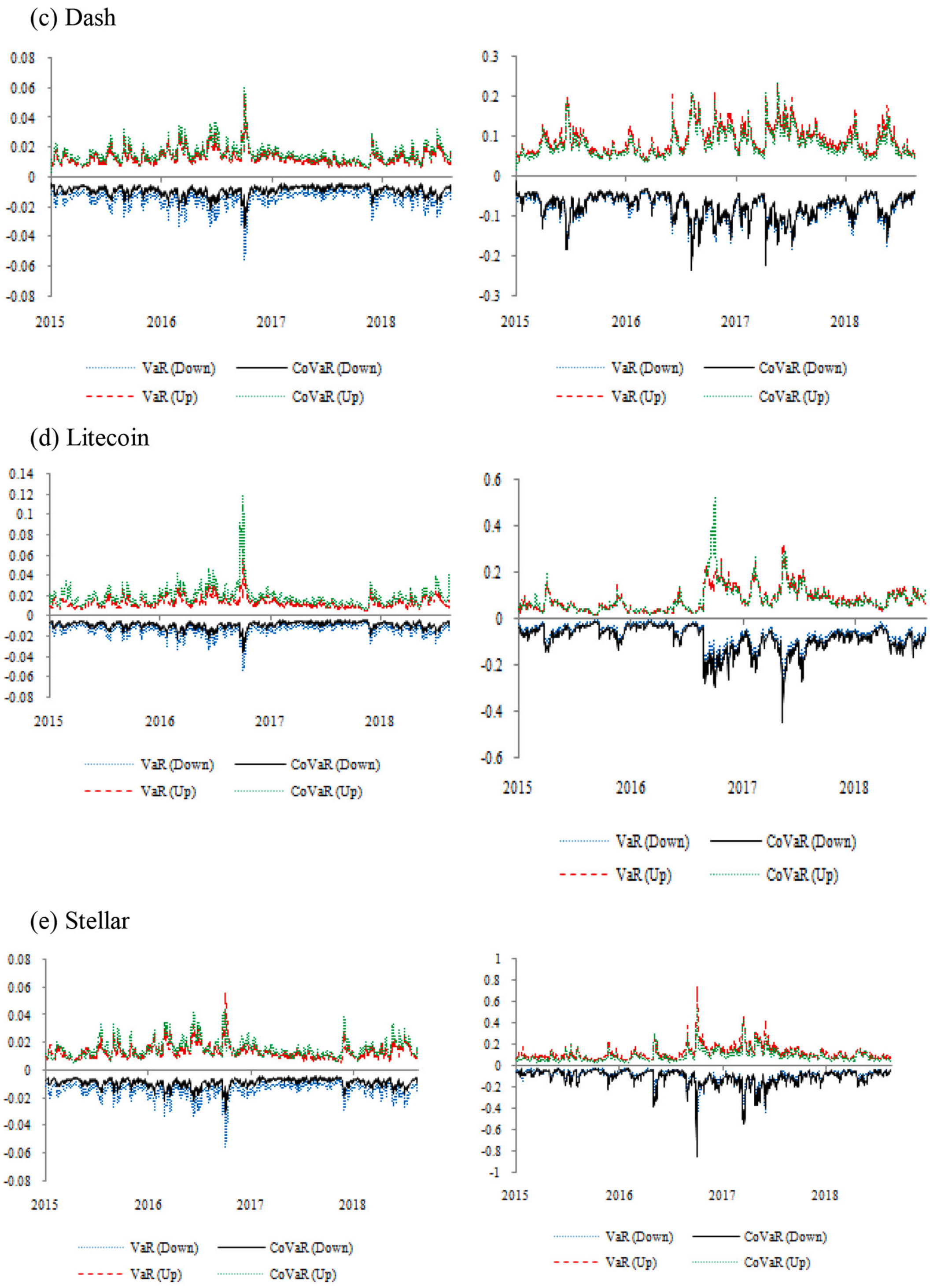


Fig. 4. (*continued*).

Americas equity index fluctuate mostly between 2016 and 2017 and in the last years of the sample period. The risk spillovers exerted by the Americas equity index on the cryptocurrencies fluctuate mostly from the middle of 2016 to the middle of 2017. This pattern, however, does not apply to the spillovers from the Americas equity index to Ethereum and NEM.

Fig. 4 shows the CoVaR and VaR spillovers from cryptocurrencies to the Europe equity index and vice versa. The spillovers from cryptocurrencies to the Europe equity index are less volatile than the risk spillovers from cryptocurrencies to the world and Americas

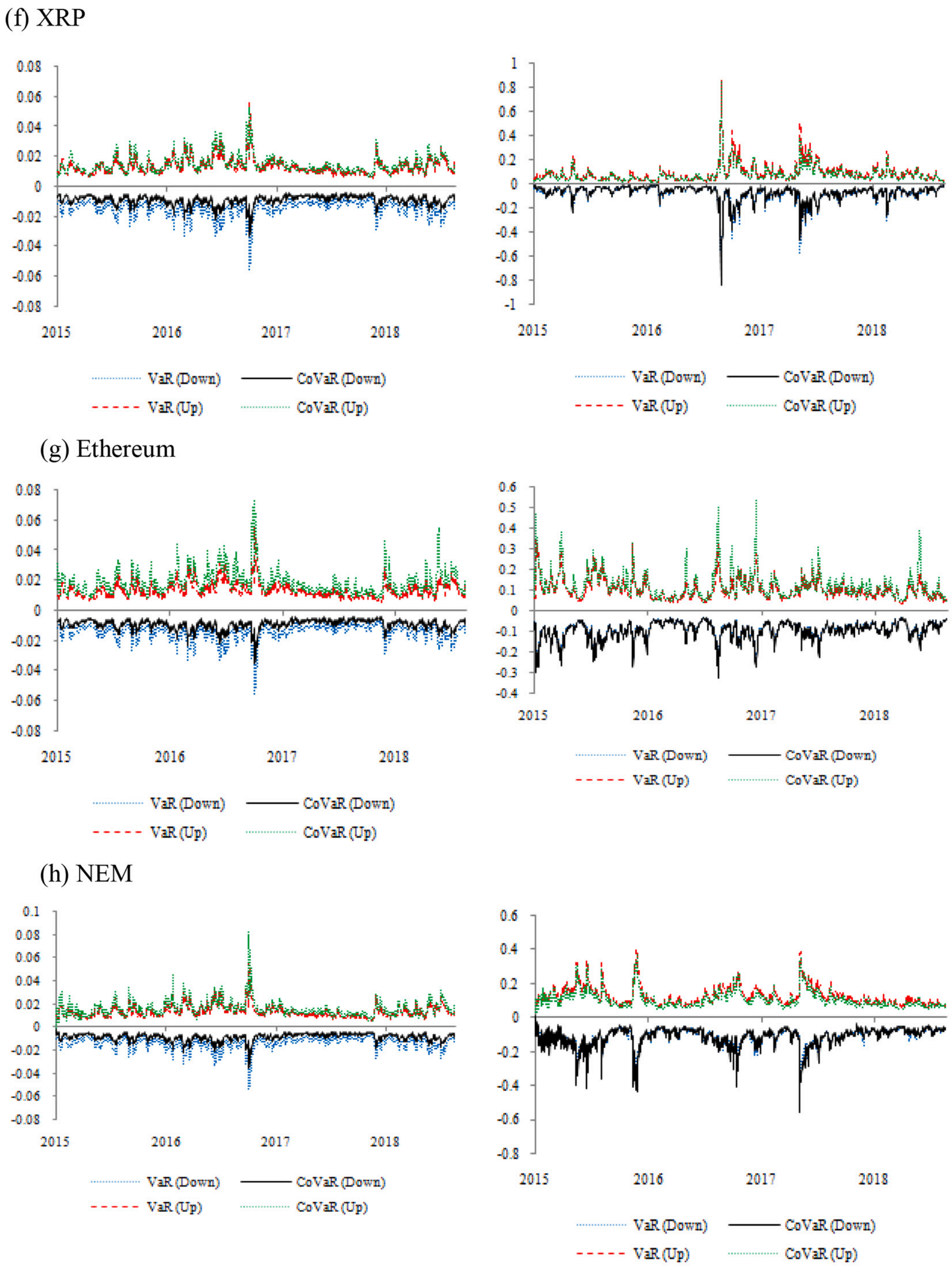


Fig. 4. (*continued*).

equity indices (displayed in Figs. 2–3), indicating distinctive volatility characteristics of these global and regional equity markets. The risk spillovers on the downside and upside from cryptocurrencies to the Europe equity index exhibit high volatility during the third quarter of 2016 only. The spillovers on the downside and upside from the Europe equity index to the cryptocurrencies are most volatile from the middle of 2016 to the middle of 2017.

Fig. 5 illustrates the CoVaR and VaR spillovers from cryptocurrencies to the Asia Pacific equity index and vice versa. The spillovers from cryptocurrencies to the Asia Pacific equity index are most volatile throughout the first and second quarters of 2016 and in the last years of the sample period. The risk spillovers exerted by the Asia Pacific equity index on the cryptocurrencies are more volatile than

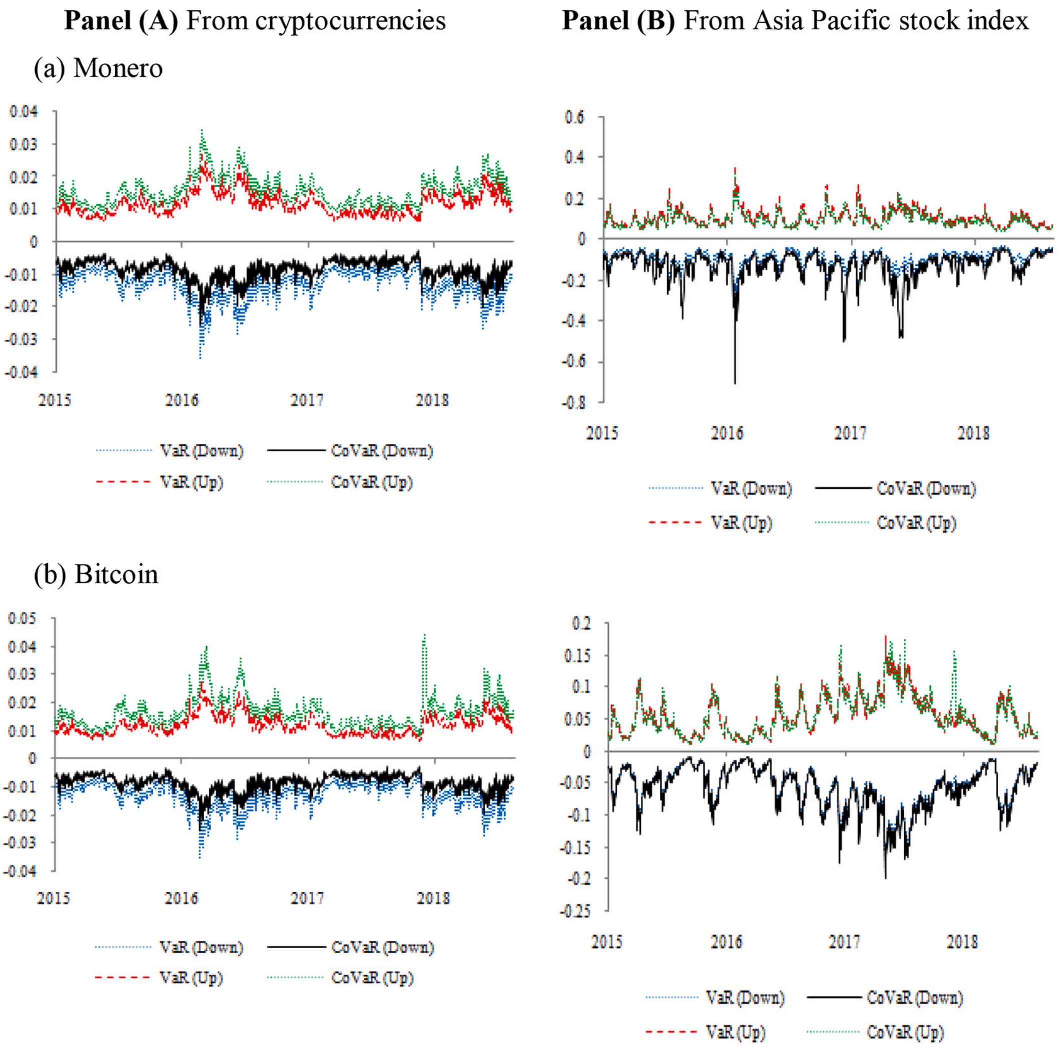


Fig. 5. Risk spillover between cryptocurrencies and Asia Pacific stock index.

that exerted by the cryptocurrencies on the equity index. The spillovers exerted by the equity index on Bitcoin, Dash, and Litecoin are most volatile from the fourth quarter of 2016 to the second quarter of 2017. The spillovers exerted on Stellar and XRP show a large volatility spike around the fourth quarter of 2016. The downside spillovers exerted on Monero are more volatile than the spillovers exerted on the upside by the Asia Pacific equity index.

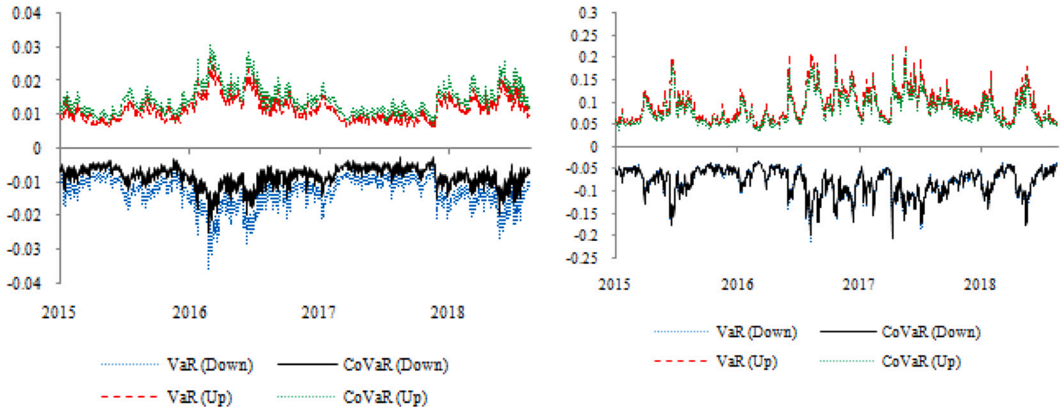
5.3. Safe-haven and hedge properties of cryptocurrencies

In this subsection, we examine the safe-haven and hedge properties of the cryptocurrencies with respect to each equity index. We also investigate the safe-haven and hedge properties of gold, silver, palladium, platinum, and diamonds for the four equity indices. Our data for rare metals and diamonds consist of the daily Gold (XAU) and Silver (XAG) Spot Multi-Contributor prices for gold and silver, respectively, Platinum Spot US Dollar rate (XPTUSD) for platinum, Palladium Spot US Dollar rate (XPDUSD) for palladium, and the Overall Diamond Index of Bloomberg (PLPH0AAI) for diamond prices. We obtain these series from DataStream and Bloomberg.

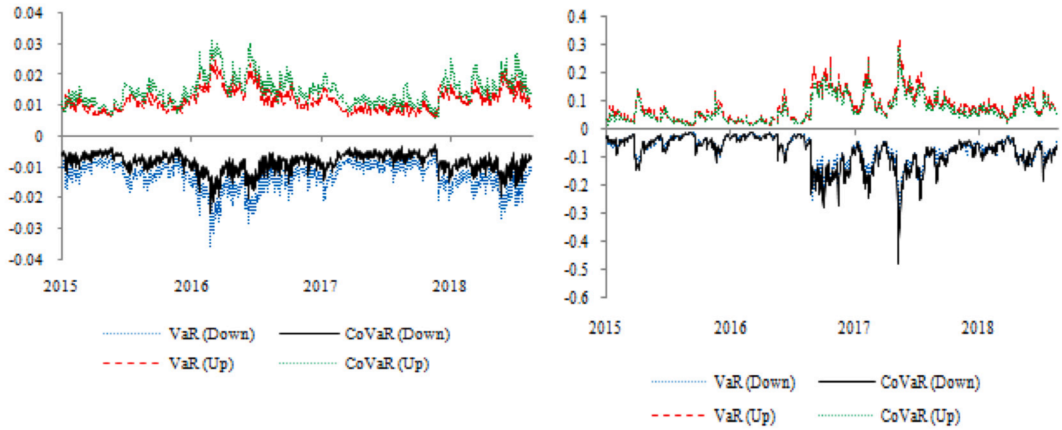
Table 7 reports the estimates of the regression models of Eqs. (21)–(22) for all assets and equity indices. Table 7 shows the estimates of b_1 and the sum of the effects for each quantile, which is $b_1 + b_2(10\%)$, $b_1 + b_2(10\%) + b_2(5\%)$, and $b_1 + b_2(10\%) + b_2(5\%) + b_2(1\%)$ for the 10%, 5%, and 1% quantiles, respectively. We identify significance with respect to the last estimated coefficient. Both Bitcoin and Litecoin act as a strong hedge for the world equity index. Besides, Dash serves as a strong safe haven against extreme 5%- and 1%-return changes of the Europe and Asia Pacific equity index, respectively.

Further, XRP exhibits a safe haven quality when the Americas equity index is at the 10% quantile and when the Europe equity index is at the 1% quantile. XRP is also a strong hedge for the Asia Pacific equity index. Finally, NEM is a safe haven for the world equity index

(c) Dash



(d) Litecoin



(e) Stellar

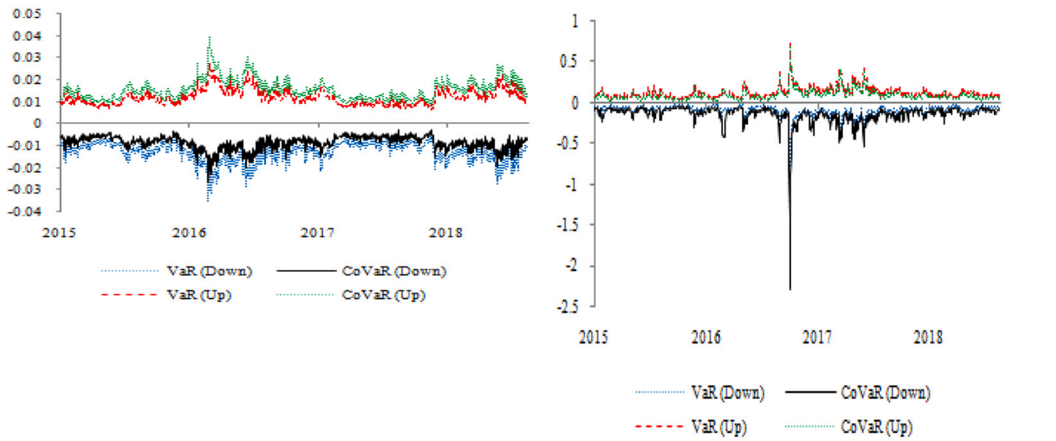


Fig. 5. (*continued*).

at the 10% quantile. As for the rare metals and diamonds, palladium is a strong hedge for the Americas equity index. In addition, diamonds are a safe haven when the world equity index is at the 10% quantile.

Table 8 presents the results of the regression models of Eqs. (21) and (23), which employ different levels of market conditional volatility as a proxy for uncertainty. Table 8 shows the estimates of b_1 and the sum of the effects for each quantile, which is $b_1 + b_2(90\%)$, $b_1 + b_2(90\%) + b_2(95\%)$, and $b_1 + b_2(90\%) + b_2(95\%) + b_2(99\%)$ for the 90%, 95%, and 99% quantiles, respectively. We

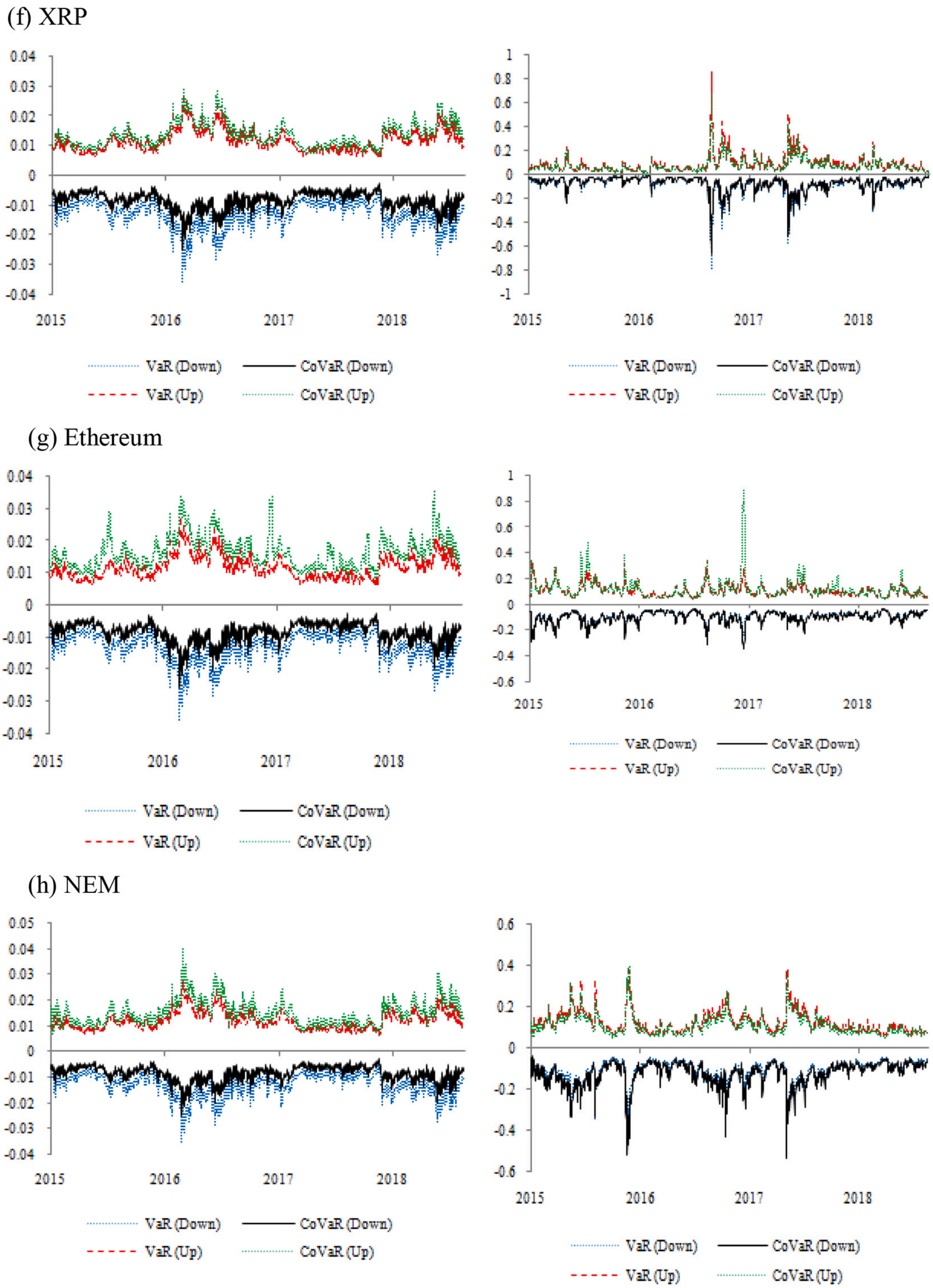


Fig. 5. (*continued*).

identify significance with respect to the last estimated coefficient. In spells of increased volatility (90%), both Bitcoin and Litecoin are a safe haven for the world equity index, Dash acts as a safe haven for the Europe equity index, and Ethereum is a safe haven for the Asia Pacific equity index. In periods of volatility exceeding 95%, Litecoin is a safe haven for the world and Americas index, Dash acts as a safe haven for the Americas index, and Monero serves as a safe haven for the Europe equity index.

Further, under extreme volatility (99%), both Litecoin and Ethereum are a safe haven for the Americas equity index, and XRP is a

Table 7
Safe-haven properties of cryptocurrencies and other assets.

	Hedge	Safe haven			Hedge	Safe haven		
	b_1	b_2(1%)	b_2(5%)	b_2(10%)	b_1	b_2(1%)	b_2(5%)	b_2(10%)
	Panel A. World equity index				Panel B. Americas equity index			
Cryptocurrencies								
Monero	0.011	−0.293	0.178	−0.632	−0.121	0.040	0.001	−0.168
BTC	−0.140*	−0.164	−0.110	0.118	−0.075	−0.122	−0.017	0.088
Dash	−0.394*	0.511***	−0.700	−0.063	−0.233	0.173	−0.203	−0.174
Litecoin	−0.233**	−0.133	−0.165	0.178**	−0.103	−0.142	0.001	−0.012
Stellar	−0.284	0.001	−0.014	−0.158	0.111	0.260	0.053	0.474
XRP	−0.049	−0.103	−0.174	−0.150	−0.068	0.246	−0.128	−0.557*
Ethereum	−0.005	0.059	−0.036	−0.310	−0.196	0.157	0.053	0.644*
NEM	0.271	0.580*	−0.544	−1.453**	−0.004	−0.048	−0.107	−0.568
Rare metals and diamonds								
Gold	−0.044	0.014	−0.063	0.040	−0.045	0.009	0.026	0.113
Silver	−0.061	−0.046	−0.038	0.048	−0.060	0.036	0.121	0.212
Platinum	−0.112	0.072	−0.058	0.185*	−0.077	0.054	0.118	0.152
Palladium	−0.098	−0.144	−0.216	−0.046	−0.150*	−0.101	0.107	0.047
Diamonds	−0.004	−0.001	0.017***	−0.110**	−0.008	0.041	−0.019	−0.042
	Panel C. Europe equity index				Panel D. Asia Pacific equity index			
Cryptocurrencies								
Monero	−0.063	0.353	−0.271	−0.574	0.097	0.435	0.016	0.537
BTC	0.020	−0.174	−0.079	−0.077	0.018	0.021*	0.189	−0.023
Dash	−0.243	−0.115	−0.130*	0.483**	−0.168	−0.397**	0.274	−0.311
Litecoin	−0.019	−0.241	0.029	−0.126	−0.086	−0.031	0.049	−0.217
Stellar	−0.124	0.135	0.248	0.235	−0.074	0.653	0.316	0.273
XRP	−0.020	−0.648**	−0.041	0.041	−0.198**	−0.005	0.264	0.002
Ethereum	0.072	0.189	0.008	−0.028	0.125	0.098	0.253	0.509
NEM	−0.011	−0.233	−0.325	−0.600	−0.275	−0.240	0.676	0.044
Rare metals and diamonds								
Gold	−0.006	0.052	0.042	0.048	0.000	−0.107	−0.136	0.019
Silver	−0.018	0.080	0.106	0.119	0.035	0.024	−0.102	0.060
Platinum	−0.062	0.025	0.077	0.114	0.049	−0.080	−0.039	0.102
Palladium	−0.084	0.124	0.148	0.115	−0.016	−0.169	0.022	0.145
Diamonds	−0.006	0.027	−0.010	0.029	−0.023	−0.015	0.028	0.056

Note: We report the estimates of the regression models of Eqs. (21)–(22) with $b_1 + b_2(10\%)$, $b_1 + b_2(10\%) + b_2(5\%)$, and $b_1 + b_2(10\%) + b_2(5\%) + b_2(1\%)$ for the 10%, 5%, and 1% quantiles, respectively. The notation ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

safe haven for the Asia Pacific equity index. As for the rare metals and diamonds, palladium is a safe haven for the Americas equity index during extreme volatility periods (99%) – in line with the results of Table 7 – and a safe haven for the Europe equity index in periods of volatility exceeding 95%. Finally, silver and diamonds are a safe haven for the Europe equity index and the Asia Pacific equity index, respectively, in periods of volatility higher than 95%.

Tables 7-8 provide evidence that Monero, Bitcoin, Dash, Litecoin, XRP, Ethereum, and NEM display safe haven or hedge properties more often than rare metals and diamonds, for all equity indices analysed. These findings are in line with Ciner et al. (2013), who documented that negative correlations between rare metals and stock returns are significant only for weekly or monthly data. The safe haven and hedge properties of palladium, silver, and diamonds for some of the indices corroborate the results of Low et al. (2016b). Therefore, most cryptocurrencies act as a strong hedge or as a safe haven for daily equity indices, consistent with Dyhrberg (2016a), Bouri et al. (2017b), Baur et al. (2018b), and Chan et al. (2019), among others.

5.4. *Out-of-sample analysis of optimal-weighting strategies*

In this subsection, we conduct an out-of-sample analysis of optimal-weighting portfolio strategies using cryptocurrencies and equity indices. We perform this analysis for rolling windows with 500 and 1000 daily returns that correspond to 829 and 329 out-of-sample periods, respectively. We calculate the downside volatility and the Omega ratio using a threshold of 0%. The terminal wealth is the accumulated wealth of a US $100 investment on the portfolio on the first forecast date under an average turnover level.

Table 9 shows the performance of the out-of-sample portfolio strategies of Eqs. (25)–(27) for a 500-rolling window. Overall, the Gumbel CET, Student-*t* CET, and rotated-Clayton CET outperform all strategies. These three strategies exhibit the highest Sortino ratio,

Table 8
Safe-haven properties of cryptocurrencies and other assets: Conditional volatility.

	Hedge	Safe haven			Hedge	Safe haven		
	b_1	b_2(90%)	b_2(95%)	b_2(99%)	b_1	b_2(90%)	b_2(95%)	b_2(99%)
	Panel A. World equity index				Panel B. Americas equity index			
Cryptocurrencies								
Monero	0.134	−0.630	−0.313	−1.805	−0.008	−0.830	0.159	−0.225
BTC	−0.084	−0.496*	−0.173	−0.135	−0.074	−0.098	−0.090	0.005
Dash	−0.184	−0.410	−0.464	−0.329	−0.186	0.295	−0.512*	0.305**
Litecoin	−0.066	−0.636***	−0.249*	−0.235	−0.024	−0.176	−0.441*	−0.008**
Stellar	0.038	−0.753	−0.937	−2.095	0.079	0.430	0.210	0.513
XRP	−0.057	−0.112	−0.181	−1.197	−0.133	0.043	−0.042	−0.009
Ethereum	0.095	−0.494	−0.030	−0.343	−0.011	0.122	0.314	−0.375**
NEM	0.072	−0.690	0.005	0.349	−0.309	0.539*	0.311	0.238
Rare metals and diamonds								
Gold	−0.019	−0.184	−0.085	0.152***	−0.010	−0.050	−0.007	0.105
Silver	−0.025	−0.257	−0.203	0.202**	0.034	−0.090	−0.138	0.240*
Platinum	−0.010	−0.098	−0.145	−0.097	0.018	−0.013	0.001	−0.155
Palladium	−0.036	−0.178	−0.405	−0.491	−0.041	−0.065	−0.051	−0.451***
Diamonds	−0.025	0.019	0.045	0.039	−0.009	−0.015	−0.001	−0.019
	Panel C. Europe equity index				Panel D. Asia Pacific equity index			
Cryptocurrencies								
Monero	−0.173	0.526*	−0.171*	1.090	0.133	0.171	0.327	0.172
BTC	−0.025	−0.145	−0.125	0.385	0.016	0.042	0.228	0.133
Dash	−0.052	−0.746**	0.096**	−0.739	−0.124	−0.476	−0.209	0.397
Litecoin	−0.002	−0.161	−0.159	0.285	−0.073	−0.127	−0.006	0.054
Stellar	−0.044	−0.071	0.208	0.383	0.162	−0.039	0.182	0.251
XRP	−0.080	−0.019	−0.115	−0.027	−0.055	−0.118	0.042	−0.621*
Ethereum	−0.063	0.324*	0.430	0.285	0.269*	−0.182**	0.086	0.567***
NEM	−0.127	−0.031	−0.607	0.706**	0.037	−0.666	0.114	−0.169
Rare metals and diamonds								
Gold	0.013	0.066	0.014	−0.071	−0.036	−0.087	−0.004	−0.011
Silver	0.043	0.125	−0.080***	−0.112	−0.001	−0.061	0.112	0.166
Platinum	0.010	0.035	−0.093	−0.141	0.008	−0.092	0.138**	0.070
Palladium	0.021	0.170*	−0.145***	−0.196	−0.053	−0.098	0.148	0.024
Diamonds	−0.004	0.074*	0.006*	0.001	0.003	−0.005	−0.054*	0.021

Note: We show the estimates of the regressions of Eqs. (21) and (23) with $b_1 + b_2(90\%)$, $b_1 + b_2(90\%) + b_2(95\%)$, and $b_1 + b_2(90\%) + b_2(95\%) + b_2(99\%)$ for the 90%, 95%, and 99% quantiles, respectively. The notation ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

Omega ratio, mean returns, and terminal wealth among all strategies. The Normal and the rotated-Gumbel CET also present high terminal wealth, Sortino and Omega ratios. Although the historical mean strategy generates the highest Sharpe ratio, it comes with a cost of the highest VaR and maximum drawdown values. Besides, the Gumbel CET, Student-*t* CET, and rotated-Clayton CET display the second, third, and fourth highest Sharpe ratio, respectively. In addition, GMV and Min-VaR portfolios have the lowest volatility, downside volatility, maximum drawdown, and CVaR among all strategies. In sum, portfolio-weighting schemes based on C-vine copulas deliver higher mean returns, terminal wealth, Sortino and Omega ratios than that of the EW and historical mean portfolios.

Table 10 illustrates the performance of the out-of-sample portfolio strategies of Eqs. (25)–(27) for a 1000-rolling window. Both Normal CET and rotated-Clayton CET show the best performance among all strategies considered. They generate the largest mean returns and terminal wealth together with the highest Sharpe, Sortino, and Omega ratios. In addition, all portfolio-weighting schemes based on C-vine copulas outperform the benchmark strategies, delivering higher Sharpe, Sortino, and Omega ratios than that of the EW and historical mean portfolios. Further, the GMV portfolios exhibit the lowest level of volatility, downside volatility, maximum drawdown, and CVaR among all strategies. Therefore, we provide evidence that the nonlinear dependence between the cryptocurrencies and the equity indices entails forward-looking measures of risk that are economically significant, which outperform benchmark strategies.

6. Conclusion

In this paper, we examine the characteristics of nonlinear dependence among eight cryptocurrencies (Monero, Bitcoin, Dash, Litecoin, Stellar, XRP, Ethereum, and NEM) through the fit of copulas with time varying parameters. We also investigate the downside

Table 9
Out-of-sample analysis of optimal-weighting portfolio strategies: 500-rolling window.

	Mean	Volatility	Downside volatility	VaR (0.05)	CVaR (0.05)	Terminal wealth	Sharpe ratio	Max drawdown	Sortino ratio	Omega ratio
Normal CET	0.434	5.933	2.865	−4.119	−9.714	1032.933	0.073	53.866	0.152	0.569
Normal Min-CVaR	0.027	0.553	0.404	−0.873	−1.404	123.568	0.049	25.177	0.067	0.150
Normal GMV	0.015	0.535	0.404	−0.874	−1.414	112.364	0.029	24.757	0.038	0.087
Clayton CET	0.434	5.957	2.897	−4.119	−9.888	1017.874	0.073	54.827	0.150	0.557
Clayton Min-CVaR	0.019	0.563	0.426	−0.888	−1.470	115.071	0.033	23.369	0.044	0.099
Clayton GMV	0.012	0.534	0.404	−0.861	−1.412	109.569	0.023	24.502	0.031	0.069
Rotated-Clayton CET	0.462	5.977	2.887	−4.193	−9.820	1274.260	0.077	60.131	0.160	0.586
Rotated-Clayton Min-CVaR	0.030	0.541	0.388	−0.904	−1.340	126.335	0.055	26.167	0.077	0.168
Rotated-Clayton GMV	0.015	0.524	0.394	−0.920	−1.378	112.191	0.029	25.153	0.039	0.086
Gumbel CET	0.538	6.334	2.878	−4.054	−9.778	2094.477	0.085	59.633	0.187	0.693
Gumbel Min-CVaR	0.027	0.560	0.405	−0.917	−1.407	123.159	0.048	25.958	0.066	0.146
Gumbel GMV	0.012	0.536	0.406	−0.905	−1.418	108.982	0.022	24.877	0.029	0.065
Rotated-Gumbel CET	0.443	5.949	2.880	−4.119	−9.791	1099.652	0.074	55.375	0.154	0.573
Rotated-Gumbel Min-CVaR	0.019	0.561	0.423	−0.866	−1.465	115.297	0.033	23.264	0.044	0.101
Rotated-Gumbel GMV	0.012	0.543	0.412	−0.876	−1.434	108.880	0.022	24.321	0.029	0.064
Student-*t* CET	0.507	6.298	2.866	−3.865	−9.714	1643.582	0.080	55.132	0.177	0.663
Student-*t* Min-CVaR	0.023	0.564	0.420	−0.866	−1.460	119.027	0.040	24.213	0.054	0.122
Student-*t* GMV	0.011	0.546	0.416	−0.885	−1.451	108.431	0.021	24.734	0.027	0.061
EW	0.225	2.821	1.856	−4.286	−6.274	465.271	0.080	83.638	0.121	0.259
Historical mean	0.313	3.256	2.041	−4.633	−6.968	862.783	0.096	84.603	0.153	0.330

Note: We report out-of-sample measures of the certainty equivalent tangency (CET), minimum conditional VaR (Min-CVaR), and global minimum variance (GMV) portfolios with cryptocurrencies and equity indices using different vine copulas. We describe these strategies on Eqs. (25)–(27). The benchmark strategies are the equally weighted (EW) and the historical mean portfolios. We calculate the downside volatility with 0% as a threshold. The terminal wealth is the accumulated wealth of a US $100 investment on the portfolio on the first forecast date under an average turnover level. The Sortino ratio is the mean return divided by the downside volatility, and the Omega ratio is the probability-weighted ratio of gains versus losses for 0% as a threshold. We use a rolling-window estimation of 500 daily returns and 829 out-of-sample periods in our analysis. The initial forecast date is Dec 19, 2016.

Table 10
Out-of-sample analysis of optimal-weighting portfolio strategies: 1000-rolling window.

	Mean	Volatility	Downside volatility	VaR (0.05)	CVaR (0.05)	Terminal wealth	Sharpe ratio	Max drawdown	Sortino ratio	Omega ratio
Normal CET	0.024	2.174	1.375	−2.646	−5.000	100.309	0.011	40.426	0.017	0.046
Normal Min-CVaR	−0.050	0.559	0.444	−0.931	−1.470	84.514	−0.089	27.308	−0.112	−0.218
Normal GMV	−0.047	0.550	0.440	−0.942	−1.456	85.369	−0.085	26.868	−0.106	−0.208
Clayton CET	−0.023	2.123	1.393	−2.646	−5.063	86.412	−0.011	42.913	−0.016	−0.043
Clayton Min-CVaR	−0.055	0.572	0.457	−1.045	−1.530	83.089	−0.096	28.390	−0.120	−0.233
Clayton GMV	−0.047	0.550	0.438	−0.962	−1.439	85.277	−0.085	27.243	−0.107	−0.209
Rotated-Clayton CET	0.022	2.184	1.381	−2.466	−5.020	99.800	0.010	36.886	0.016	0.043
Rotated-Clayton Min-CVaR	−0.049	0.566	0.441	−1.023	−1.424	84.648	−0.087	28.018	−0.111	−0.212
Rotated-Clayton GMV	−0.046	0.547	0.434	−0.967	−1.422	85.413	−0.085	27.028	−0.107	−0.207
Gumbel CET	−0.016	2.128	1.384	−2.646	−5.061	88.252	−0.008	42.997	−0.012	−0.031
Gumbel Min-CVaR	−0.051	0.564	0.443	−0.964	−1.438	84.198	−0.090	27.820	−0.114	−0.220
Gumbel GMV	−0.046	0.548	0.437	−0.953	−1.438	85.505	−0.084	26.807	−0.105	−0.206
Rotated-Gumbel CET	−0.015	2.140	1.392	−2.646	−5.053	88.548	−0.007	44.716	−0.011	−0.028
Rotated-Gumbel Min-CVaR	−0.055	0.572	0.459	−1.027	−1.534	83.026	−0.096	28.438	−0.120	−0.234
Rotated-Gumbel GMV	−0.046	0.552	0.440	−0.948	−1.450	85.417	−0.084	27.092	−0.105	−0.206
Student-*t* CET	−0.007	2.126	1.372	−2.646	−4.982	91.040	−0.003	40.663	−0.005	−0.013
Student-*t* Min-CVaR	−0.054	0.564	0.450	−0.969	−1.499	83.309	−0.096	28.082	−0.120	−0.233
Student-*t* GMV	−0.049	0.552	0.442	−0.939	−1.460	84.759	−0.088	27.198	−0.110	−0.216
EW	−0.285	2.030	1.648	−3.971	−5.364	36.502	−0.140	71.028	−0.173	−0.328
Historical mean	−0.292	2.153	1.735	−3.971	−5.648	35.396	−0.136	72.613	−0.168	−0.318

Note: We report out-of-sample measures of the certainty equivalent tangency (CET), minimum conditional VaR (Min-CVaR), and global minimum variance (GMV) portfolios with cryptocurrencies and equity indices using different vine copulas. We describe these strategies on Eqs. (25)–(27). The benchmark strategies are the equally weighted (EW) and the historical mean portfolios. We calculate the downside volatility with 0% as a threshold. The terminal wealth is the accumulated wealth of a US $100 investment on the portfolio on the first forecast date under an average turnover level. The Sortino ratio is the mean return divided by the downside volatility, and the Omega ratio is the probability-weighted ratio of gains versus losses for 0% as a threshold. We use a rolling-window estimation of 1000 daily returns and 329 out-of-sample periods in our analysis. The initial forecast date is May 3, 2018.

and upside risk spillovers between cryptocurrencies and global and regional equity markets (world, Americas, Europe, and Asia Pacific) using a CoVaR method.

Our results provide evidence of symmetry and asymmetry in the dependence dynamics of the cryptocurrencies, with the symmetric dynamics being more predominant. NEM and Ethereum exert the largest downside and upside CoVaR spillovers on the world equity index. In contrast, the largest downside CoVaR spillovers from the world equity index to the cryptocurrencies are to NEM and Stellar, while the largest upside CoVaR spillovers from the world equity index to the cryptocurrencies are to Ethereum and NEM. Stellar and Bitcoin exert the largest downside and upside CoVaR spillovers on the Americas equity index. The largest downside CoVaR spillovers from the Americas equity index to the cryptocurrencies are to Stellar and NEM, and the largest upside CoVaR spillovers from the Americas equity index to the cryptocurrencies are to Ethereum and NEM. The largest downside CoVaR spillovers on the Europe equity index are exerted by Bitcoin, Litecoin and Ethereum, and those on the upside are exerted by Litecoin and Ethereum. In contrast, the largest downside CoVaR spillovers from the Europe equity index to the cryptocurrencies are to NEM and Stellar, while on the upside, the largest spillovers are from the index to Ethereum and NEM. Stellar and Monero exert the largest downside CoVaR spillovers on the Asia Pacific equity index, and Bitcoin and Ethereum exert those on the upside. In contrast, the largest downside CoVaR spillovers from the Asia Pacific equity index to the cryptocurrencies are to Stellar and Monero, while those on the upside are to Ethereum and NEM.

In addition, we verify the safe-haven and hedge properties of the eight cryptocurrencies with respect to each equity index. For comparison purposes, we also examine the safe-haven and hedge properties of gold, silver, palladium, platinum, and diamonds for the four equity indices. We find that Monero, Bitcoin, Dash, Litecoin, XRP, Ethereum, and NEM exhibit safe haven or hedge properties more often than rare metals and diamonds, for daily equity indices analysed, consistent with Dyhrberg (2016a), Bouri et al. (2017b), Baur et al. (2018b), and Chan et al. (2019), among others.

We also employ canonical vine (C-vine) copulas (Bedford and Cooke, 2002; Kurowicka and Cooke, 2006; Aas et al., 2009; Czado et al., 2012) for modelling the dependence among the twelve assets. We show that portfolio-weighting schemes based on C-vine copulas outperform benchmark strategies. Our results are robust for different rolling-window sizes. Overall, we provide evidence that the nonlinear dependence between the cryptocurrencies and the equity indices entails forward-looking measures of risk that are economically significant, which outperform benchmark strategies. Therefore, our findings are useful for the design of investment currency positions.

Data availability statement

The data that support the findings of this study are available on request to the corresponding author. We obtained all cryptocurrency price series from https://coinmarketcap.com/ and all equity index series from DataStream. We gathered the rare metal and diamond price series from DataStream and Bloomberg.

CRediT authorship contribution statement

Waqas Hanif: Conceptualization, Methodology, Software, Formal analysis, Investigation, Visualization, Writing – original draft. **Jose Areola Hernandez:** Conceptualization, Data curation, Formal analysis, Writing – original draft, Validation. **Victor Troster:** Formal analysis, Software, Validation, Writing – review & editing, Funding acquisition. **Sang Hoon Kang:** Conceptualization, Formal analysis, Methodology, Software, Resources, Visualization. **Seong-Min Yoon:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pacfin.2022.101822.

References

Aas, K., Czado, C., Frigessi, A., Bakken, H., 2009. Pair-copula constructions of multiple dependence. Insurance 44, 182–198.
Abadie, A., 2002. Bootstrap tests for distributional treatment effects in instrumental variable models. J. Am. Stat. Assoc. 97, 284–292.
Adrian, T., Brunnermeier, M.K., 2016. CoVaR. Am. Econ. Rev. 106, 1705–1741.
Al-Yahyaee, K.H., Mensi, W., Al-Jarrah, I.M.W., Hamdi, A., Kang, S.H., 2019. Volatility forecasting, downside risk, and diversification benefits of Bitcoin and oil and international commodity markets: a comparative analysis with yellow metal. N. Am. J. Econ. Financ. 49, 104–120.
Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2019. Cryptocurrency market contagion: market uncertainty, market complexity, and dynamic portfolios. J. Int. Financ. Mark. Inst. Money 61, 37–51.
Anyfantaki, S., Arvanitis, S., Topaloglou, N., 2019. Diversification. In: Integration and Cryptocurrency Market.
Artzner, P., Delbaen, F., Eber, J.M., Heath, D., 1999. Coherent measures of risk. Math. Financ. 9, 203–228.
Auer, B.R., Schuhmacher, F., 2013. Diamonds - a precious new asset? Int. Rev. Financ. Anal. 28, 182–189.
Barbi, M., Geman, H., Romagnoli, S., 2020. Diamonds and precious metals for reduction of portfolio tail risk. Appl. Econ. 52, 2841–2861.
Baumöhl, E., 2019. Are cryptocurrencies connected to forex? A quantile cross-spectral approach. Financ. Res. Lett. 29, 363–372.
Baur, D.G., Lucey, B.M., 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financ. Rev. 45, 217–229.
Baur, D.G., McDermott, T.K., 2010. Is gold a safe haven? International evidence. J. Bank. Financ. 34, 1886–1898.
Baur, D.G., Dimpfl, T., Kuck, K., 2018a. Bitcoin, gold and the US dollar - a replication and extension. Financ. Res. Lett. 25, 103–110.
Baur, D.G., Hong, K.H., Lee, A.D., 2018b. Bitcoin: medium of exchange or speculative assets? J. Int. Financ. Mark. Inst. Money 54, 177–189.

Bedford, T., Cooke, R.M., 2002. Vines - a new graphical model for dependent random variables. Ann. Stat. 30, 1031–1068.
Beneki, C., Koulis, A., Kyriazis, N.A., Papadamou, S., 2019. Investigating volatility transmission and hedging properties between Bitcoin and Ethereum. Res. Int. Bus. Financ. 48, 219–227.
Bernal, O., Gnabo, J.Y., Guilmin, G., 2014. Assessing the contribution of banks, insurance and other financial services to systemic risk. J. Bank. Financ. 47, 270–287.
Bouoiyour, J., Selmi, R., 2017. Ether: Bitcoin's Competitor or Ally?.
Bouri, E., Gupta, R., Tiwari, A.K., Roubaud, D., 2017a. Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Financ. Res. Lett. 23, 87–95.
Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.I., 2017b. On the hedge and safe haven properties of bitcoin: is it really more than a diversifier? Financ. Res. Lett. 20, 192–198.
Bouri, E., Hussain Shahzad, S.J., Roubaud, D., 2020a. Cryptocurrencies as hedges and safe-havens for US equity sectors. Q. Rev. Econ. Fin. 75, 294–307.
Bouri, E., Lucey, B., Roubaud, D., 2020b. Cryptocurrencies and the downside risk in equity investments. Financ. Res. Lett. 33, 101211.
Bouri, E., Roubaud, D., Shahzad, S.J.H., 2020c. Do Bitcoin and other cryptocurrencies jump together? Q. Rev. Econ. Fin. 76, 396–409.
Brière, M., Oosterlinck, K., Szafarz, A., 2015. Virtual currency, tangible return: portfolio diversification with bitcoin. J. Asset Manag. 16 (6), 365–373.
Chan, W.H., Le, M., Wu, Y.W., 2019. Holding Bitcoin longer: the dynamic hedging abilities of Bitcoin. Q. Rev. Econ. Fin. 71, 107–113.
Charfeddine, L., Benlagha, N., Maouchi, Y., 2020. Investigating the dynamic relationship between cryptocurrencies and conventional assets: implications for financial investors. Econ. Model. 85, 198–217.
Ciner, C., Gurdgiev, C., Lucey, B.M., 2013. Hedges and safe havens: an examination of stocks, bonds, gold, oil and exchange rates. Int. Rev. Financ. Anal. 29, 202–211.
Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econ. Lett. 165, 28–34.
Czado, C., Schepsmeier, U., Min, A., 2012. Maximum likelihood estimation of mixed C-vines with application to exchange rates. Stat. Model. 12, 229–255.
Dyhrberg, A.H., 2016a. Hedging capabilities of bitcoin. Is it the virtual gold? Financ. Res. Lett. 16, 139–144.
Dyhrberg, A.H., 2016b. Bitcoin, gold and the dollar - a GARCH volatility analysis. Financ. Res. Lett. 16, 85–92.
Eisl, A., Gasser, S.M., Weinmayer, K., 2015. Caveat Emptor: Does Bitcoin Improve Portfolio Diversification? SSRN Electronic Journal. Elsevier BV. https://doi.org/10.2139/ssrn.2408997.
Fisch, C., 2019. Initial coin offerings (ICOs) to finance new ventures. J. Bus. Ventur. 34, 1–22.
Giudici, P., Abu-Hashish, I., 2019. What determines bitcoin exchange prices? A network VAR approach. Financ. Res. Lett. 28, 309–318.
Guesmi, K., Saadi, S., Abid, I., Ftiti, Z., 2019. Portfolio diversification with virtual currency: evidence from bitcoin. Int. Rev. Financ. Anal. 63, 431–437.
Hansen, B.E., 1994. Autoregressive conditional density estimation. Int. Econ. Rev. 35, 705–730.
Ji, Q., Bouri, E., Gupta, R., Roubaud, D., 2018. Network causality structures among Bitcoin and other financial assets: a directed acyclic graph approach. Q. Rev. Econ. Fin. 70, 203–213.
Kajtazi, A., Moro, A., 2019. The role of bitcoin in well diversified portfolios: a comparative global study. Int. Rev. Financ. Anal. 61, 143–157.
Kang, S.H., McIver, R.P., Hernandez, J.A., 2019. Co-movements between Bitcoin and Gold: a wavelet coherence analysis. Phys. A Stat. Mech. Appl. 536, 120888.
Karimalis, E.N., Nomikos, N.K., 2018. Measuring systemic risk in the European banking sector: a copula CoVaR approach. Eur. J. Financ. 24, 944–975.
Klein, T., Pham Thu, H., Walther, T., 2018. Bitcoin is not the New Gold – a comparison of volatility, correlation, and portfolio performance. Int. Rev. Financ. Anal. 59, 105–116.
Kliber, A., Marszałek, P., Musiałkowska, I., Świerczyńska, K., 2019. Bitcoin: safe haven, hedge or diversifier? Perception of bitcoin in the context of a country's economic situation — a stochastic volatility approach. Phys. A Stat. Mech. Appl. 524, 246–257.
Kurowicka, D., Cooke, R., 2006. Uncertainty Analysis With High Dimensional Dependence Modelling, Wiley Series in Probability and Statistics. John Wiley and Sons Ltd., Chichester.
Low, R.K.Y., 2018. Vine copulas: modelling systemic risk and enhancing higher-moment portfolio optimisation. Account. Finance 58, 423–463.
Low, R., Marsh, T., 2019. Cryptocurrency and blockchains: retail to institutional. J. Invest. 29, 18–30.
Low, R.K.Y., Alcock, J., Faff, R., Brailsford, T., 2013. Canonical vine copulas in the context of modern portfolio management: are they worth it? J. Bank. Financ. 37, 3085–3099.
Low, R.K.Y., Faff, R., Aas, K., 2016a. Enhancing mean-variance portfolio selection by modeling distributional asymmetries. J. Econ. Bus. 85, 49–72.
Low, R.K.Y., Yao, Y., Faff, R., 2016b. Diamonds vs. precious metals: what shines brightest in your investment portfolio? Int. Rev. Financ. Anal. 43, 1–14.
Lucey, B.M., Li, S., 2015. What precious metals act as safe havens, and when? Some US evidence. Appl. Econ. Lett. 22, 35–45.
Manner, H., Reznikova, O., 2012. A survey on time-varying copulas: specification, simulations, and application. Econ. Rev. 31, 654–687.
Markowitz, H., 1952. Portfolio selection. J. Financ. 7, 77–91.
Marsh, T., Low, R., 2019. Cryptocurrency: tulip mania or digital promise for the millennial generation? Stud. Econ. Financ. 36, 2–7.
Mensi, W., Sensoy, A., Aslan, A., Kang, S.H., 2019. High-frequency asymmetric volatility connectedness between Bitcoin and major precious metals markets. N. Am. J. Econ. Financ. 50, 101031.
Merton, R.C., 1980. On estimating the expected return on the market: an exploratory investigation. J. Financ. Econ. 8, 323–361.
Patton, A.J., 2006. Modelling asymmetric exchange rate dependence. Int. Econ. Rev. 47, 527–556.
Patton, A.J., 2012. A review of copula models for economic time series. J. Multivar. Anal. 110, 4–18.
Phillip, A., Chan, J., Peiris, S., 2018. A new look at cryptocurrencies. Econ. Lett. 163, 6–9.
Platanakis, E., Urquhart, A., 2020. Should investors include Bitcoin in their portfolios? A portfolio theory approach. Br. Account. Rev. 52, 100837.
Rad, H., Low, R.K.Y., Miffre, J., Faff, R., 2020. Does sophistication of the weighting scheme enhance the performance of long-short commodity portfolios? J. Empir. Financ. 58, 164–180.
Reboredo, J.C., Ugolini, A., 2016. Quantile dependence of oil price movements and stock returns. Energy Econ. 54, 33–49.
Rockafellar, R.T., Uryasev, S., 2000. Optimization of conditional value-at-risk. J. Risk 2, 21–42.
Rockafellar, R.T., Uryasev, S., 2002. Conditional value-at-risk for general loss distributions. J. Bank. Financ. 26, 1443–1471.
Sahamkhadam, M., Stephan, A., 2020. Portfolio Optimization Based on Forecasting Models Using Vine Copulas: An Empirical Assessment for the Financial Crisis. SSRN Electronic Journal. Elsevier BV. https://doi.org/10.2139/ssrn.3507936.
Sahamkhadam, M., Stephan, A., Östermark, R., 2018. Portfolio optimization based on GARCH-EVT-copula forecasting models. Int. J. Forecast. 34, 497–506.
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 Econ. 74, 787–801.
Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., Lucey, B., 2019. Is Bitcoin a better safe-haven investment than gold and commodities? Int. Rev. Financ. Anal. 63, 322–330.
Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., 2020. Safe haven, hedge and diversification for G7 stock markets: gold versus bitcoin. Econ. Model. 87, 212–224.
Sklar, A., 1959. Fonctions de répartition à n dimensions et leurs marges, 8. Publications de L'Institut de Statistique de L'Université de Paris, pp. 229–231.
Smales, L.A., 2019. Bitcoin as a safe haven: is it even worth considering? Financ. Res. Lett. 30, 385–393.
Stensås, A., Nygaard, M.F., Kyaw, K., Treepongkaruna, S., 2019. Can Bitcoin be a diversifier, hedge or safe haven tool? Cogent Econ. Financ. 7, 1593072.
Symitsi, E., Chalvatzis, K.J., 2019. The economic value of Bitcoin: a portfolio analysis of currencies, gold, oil and stocks. Res. Int. Bus. Financ. 48, 97–110.
Tiwari, A.K., Adewuyi, A.O., Albulescu, C.T., Wohar, M.E., 2020. Empirical evidence of extreme dependence and contagion risk between main cryptocurrencies. N. Am. J. Econ. Financ. 51, 101083.
Urquhart, A., 2016. The inefficiency of Bitcoin. Econ. Lett. 148, 80–82.
Yermack, D., 2015. Is bitcoin a real currency? An economic appraisal. In: Chuen, D.L.K. (Ed.), Handbook of Digital Currency: Bitcoin, Innovation, Financial Instruments, and Big Data. Elsevier Inc., pp. 31–43