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Relationships among return and liquidity of cryptocurrencies

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Abstract

The cryptocurrency market is a complex and rapidly evolving financial landscape in which understanding the inter- and intra-asset dependencies among key financial variables, such as return and liquidity, is crucial. In this study, we analyze daily return and liquidity data for six major cryptocurrencies, namely Bitcoin, Ethereum, Ripple, Binance Coin, Litecoin, and Dogecoin, spanning the period from June 3, 2020, to November 30, 2022. Liquidity is estimated using three low-frequency proxies: the Amihud ratio and the Abdi and Ranaldo (AR) and Corwin and Schultz (CS) estimators. To account for autoregressive and persistent effects, we apply the autoregressive integrated moving average-generalized autoregressive conditional heteroscedasticity (ARIMA-GARCH) model and subsequently utilize the copula method to examine the interdependent relationships between the return on and liquidity of the six cryptocurrencies. Our analysis reveals strong cross-asset lower-tail dependence in return and significant cross-asset upper-tail dependence in illiquidity measures, with more pronounced dependence observed in specific cryptocurrency pairs, primarily involving Bitcoin, Ethereum, and Litecoin. We also observe that returns tend to be higher when liquidity is lower in the cryptocurrency market. Our findings have significant implications for portfolio diversification, asset allocation, risk management, and trading strategy development for investors and traders, as well as regulatory policy-making for regulators. This study contributes to a deeper understanding of the cryptocurrency marketplace and can help inform investment decision making and regulatory policies in this emerging financial domain.

Keywords: Cryptocurrency, Liquidity, Dependence structure, Stationary, ARIMA-GARCH model, Copula model

Introduction

The study of cross-asset dependence structure among financial variables has been a topic of considerable interest in the modern financial industry and academic circles, with a rich research history owing to its critical implications in portfolio-risk management (Markowitz 1952), technical and fundamental asset-trading strategies (Vidyamurthy 2004), regulatory policies for handling systemic financial risks (Hartmann et al. 2004), and various other applications (So et al. 2022). While limiting dependence to the linear regime is a common practice and is adequate in many situations, a general non-linear dependence structure offers deeper insights into the complex and interconnected nature of financial markets (Righi and Ceretta 2013; Mokni and Mansouri 2017), as linear methods may fail to capture the complete range of relationships between financial variables (Hartman and Hlinka 2018; Zhang 2021). Among the many methods for analyzing non-linear dependence structure, copula models are frequently used to estimate general correlations among financial variables, offering the notable advantage of separating the dependence structure from marginal distributions (Fermanian 2017). Therefore, in this study, we focus on utilizing copula models to investigate the interdependence structure among financial variables in the newly established cryptocurrency market.

Cryptocurrencies, which are virtual assets that use blockchain technology (Xu et al. 2019), are rapidly gaining popularity among investors, traders, and traditional financial institutions such as banks as the demand for cryptocurrency-based services continues to rise (Auer et al. 1013). As of December 2022, the total value of the cryptocurrency market is estimated to be approximately 0.85 trillion, with over 20,000 cryptocurrencies listed on the CoinMarketCap website.[1] Moreover, financial derivatives such as options and futures are designed and traded on crypto exchanges (Geman and Price 2021; Zulfiqar and Gulzar 2021). Despite the increasing popularity of cryptocurrencies, this rapidly evolving market remains highly volatile and lacks effective regulatory measures (Pace and Rao 2023; Zetzsche et al. 2018; Cumming et al. 2019; Chokor and Alfieri 2021). This high volatility is evident in the numerous liquidity crises faced by cryptocurrency institutions, leading to the decline of multiple cryptocurrencies (Gudgeon et al. 2020). Given the young and complex nature of the cryptocurrency market, revealing dependence structures among major cryptocurrencies is crucial. In this study, we focus on understanding the inter- and intra-asset dependence of two critical financial variables in the cryptocurrency market: return and liquidity. Our study aims to shed light on the underlying complexities and interconnectedness of the cryptocurrency market, and to offer valuable insights for market participants and regulators in managing risks and developing effective investment and regulatory strategies.

The study of cross-asset tail dependence in return has been a topic of extensive research in the cryptocurrency market. For instance, Tiwari et al. (2020) found strong upper- and lower-tail dependence in each asset pair formed by Bitcoin (BTC), Litecoin (LTC), and Ripple (XRP) for the period from 08–04–2013 to 06–17–2018. Similarly, Boako et al. (2019) established strong dependence among the returns on BTC and those on five other altcoins [Dash, Ethereum (ETH), LTC, XRP, and Stellar] for a similar period from September 2015 to June 2018. Moreover, the knowledge of tail dependence has been applied by Syuhada and Hakim (2020), Pradhan et al. (2021), and Tenkam et al. (2022) in constructing cryptocurrency portfolios covering the data period from September 2016 to April 2022. Additionally, several studies have investigated the correlations between returns on BTC and those on traditional stock, forex, and gold markets to diversify and hedge risks (Garcia-Jorcano and Benito 2020; Hussain et al. 2019; Kim et al. 2020; Chen and So 2020; Owais and Gulzar 2020; Qarni and Gulzar 2021), using return data before September 2020. Further literature on cross-asset return dependence in the cryptocurrency market will be reviewed later in this study.

[1] https://coinmarketcap.com.

Market liquidity, defined as the ease, speed, and affordability with which an asset can be traded in the market, significantly impacts the determination of systemic liquidity risk in a financial system through its link to funding liquidity (Brunnermeier and Pedersen 2009), particularly since the 2008 financial crisis (Brunnermeier and Pedersen 2009). Adequate liquidity results in a stable market with minimal price fluctuations, whereas inadequate liquidity can lead to substantial market volatility and price spikes. The liquidity levels of different cryptocurrencies can vary significantly and are strongly interconnected, such that a liquidity shortage in one digital asset may lead to considerable increases or decreases in demand for other digital assets, as evidenced by several empirical studies (Gama Silva et al. 2019; Manahov 2021; Anciaux et al. 2021; Hasan et al. 2022; Tripathi et al. 2022). Consequently, a comprehensive understanding of the general dependence structure among them is crucial for investors to optimize portfolios, traders to devise optimal trading strategies, and authorized regulators and financial institutions to manage systemic liquidity risk (End and Tabbae 2012). However, only a few studies have examined the cross-asset liquidity dependence of cryptocurrencies in the context of liquidity commonality and connectedness (Anciaux et al. 2021; Hasan et al. 2022; Tripathi et al. 2022; Ahmed 2022), which are limited to the linear regime. This study seeks to provide a more in-depth analysis of the interdependencies among cryptocurrencies' liquidity and their implications for investment strategies and regulatory policies by utilizing advanced non-linear methods, such as the copula approach, to analyze the dependence structure.

Moreover, an asset's liquidity and return are strongly interconnected, as liquidity fluctuations can affect price discovery and overall market stability (Hasbrouck and Seppi 2001). Illiquid assets typically exhibit higher returns due to the liquidity-risk premium associated with the difficulties in buying or selling them in a timely manner (Amihud 2002). Furthermore, periods of low liquidity can exacerbate price volatility, leading to significant fluctuations in asset returns. In the context of cryptocurrencies, understanding the relationship between liquidity and return is particularly crucial given the market's inherent volatility, inefficiencies, and unique investor sentiments (Fang et al. 2022). Previous studies on return-volume relationships (Naeem et al. 2020a, 2020b; Chan et al. 2022; Leirvik 2022) and cryptocurrency liquidity during periods of extreme price movements (Manahov 2021; Zhang et al. 2020) also fall into this category. In this study, we aim to directly investigate the general return-liquidity relationships and compare the resulting economic implications with those from previous research.

The current literature on cross-asset tail dependence in cryptocurrency returns (Tiwari et al. 2020; Boako et al. 2019; Syuhada and Hakim 2020; Pradhan et al. 2021; Tenkam et al. 2022; Garcia-Jorcano and Benito 2020; Hussain et al. 2019; Kim et al. 2020; Chen and So 2020) is mostly outdated, while studies on liquidity levels (Anciaux et al. 2021; Hasan et al. 2022; Tripathi et al. 2022; Ahmed 2022) are limited to the linear regime. Furthermore, studies on return-volume relationships (Naeem et al. 2020a, 2020b; Chan et al. 2022) only serve as indirect indicators for general return-liquidity correlations. In this study, we complement these studies by employing widely used copula models to investigate the inter-asset dependency structure of liquidity proxies and returns, as well as intra-asset liquidity-return correlations among six major cryptocurrencies [BTC, ETH, XRP, Binance coin (BNB), LTC, and Dogecoin (DOGE)] for the period from

03–06–2020 to 11–30–2022. To better quantify liquidity levels, we use three different illiquidity proxies derived from low-frequency transaction data: the Amihud ratio (Amihud 2002), characterizing the price impact, and two estimators for the bid-ask spread (BAS), representing transaction costs, i.e., the Abdi and Ranaldo (AR) (2017) and Corwin and Schultz (CS) estimators (Corwin and Schultz 2012). We employ the method of vine copulas (Czado 2019) to provide a robust way of analyzing the general dependence structure among these liquidity variables and returns beyond the limitations of linear correlation analyses. Our study contributes to the literature by providing updated and more comprehensive analyses of the inter- and intra-asset dependence of liquidity and returns in the cryptocurrency market, which can be valuable to market participants and regulators in portfolio optimization, risk management, and regulatory policy making.

Our study makes several contributions to the literature on the dependence structure of the cryptocurrency market. First, by employing copula models, we enable a more comprehensive analysis of the general dependence structure among liquidity proxies and returns on major cryptocurrencies, transcending linear correlation analyses. Second, we provide up-to-date and robust evidence on cross-asset lower-tail dependence in returns and cross-asset upper-tail dependence in illiquidity proxies for six major cryptocurrencies, revealing stronger correlations in select cryptocurrency pairs, predominantly involving BTC, ETH, and LTC. Third, our analysis reveals that return-liquidity correlations in the cryptocurrency market are similar to those in traditional markets, with lower liquidity levels being associated with higher returns.

The identified cross-asset dependence structure in the returns on and liquidity of cryptocurrencies has valuable implications for portfolio-risk management, trading-strategy optimization (Fang et al. 2022; Sebastião and Godinho 2021), and regulatory policy enhancement (Zetzsche et al. 2018; Cumming et al. 2019; Chokor and Alfieri 2021). By incorporating liquidity as a factor, investors can make more informed decisions regarding market entry and exit, while traders can optimize their multi-asset trading strategies. Moreover, regulators can better assess market stability during liquidity crises and evaluate the effectiveness of current policies in managing systemic risks. Furthermore, the discovered liquidity-dependence structure can assist financial institutions in determining liquidity requirements for crypto collateral and derivatives. This study offers valuable insights to a wide range of stakeholders, including researchers, practitioners, investors, traders, and regulators, contributing to the growing body of research on cryptocurrencies and their complex interconnectedness. The findings can help foster a more efficient and transparent digital market, thereby mitigating hidden downside risks and preventing the occurrence of systemic crashes.

The remainder of the paper is organized as follows: Section "Literature review" introduces some previous related research, Section "Data and variables" describes the data and financial variables for the selected cryptocurrencies, while the methodologies are presented in Section "Methodologies". Autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroscedasticity (GARCH) modeling are discussed in Sections "ARIMA modeling" and "GARCH modeling", respectively. The final results of the examination of asset and return-liquidity relationships using copulae are analyzed in Section "Copula Modeling". Finally, the paper concludes in the last section.

Literature review

The extensive body of literature on blockchain technology and the cryptocurrency market offers comprehensive insights into the evolution and application of these technologies. For a more in-depth understanding, readers are encouraged to explore comprehensive reviews such as those provided by Xu et al. (2019) and Fang et al. (2022). The genesis of blockchain technology is largely attributed to Nakamoto's seminal whitepaper, published in 2008 (Nakamoto 2008). This seminal work introduced Bitcoin as the first application of this revolutionary technology. Originally envisaged as a decentralized, peer-to-peer system facilitating digital transactions, the scope of blockchain technology has substantially expanded beyond its initial financial function. The range of its applications now spans numerous sectors including, but not limited to, smart contracts (Hewa et al. 2021), supply-chain management (Queiroz et al. 2020), smart cities (Sun et al. 2016), healthcare (Engelhardt 2017), and the Internet of Things (Dai et al. 2019). A systematic analysis of 756 blockchain-related scholarly articles conducted by Xu et al. (2019), found that the field of business and economics was among the most frequently discussed topics. Within this domain, the research theme of "initial coin offerings" associated with cryptocurrencies was identified as one of the top five areas of interest (Adhami et al. 2018; Ante et al. 2018; Fisch 2019). This underscores the pervasive impact of blockchain technology and cryptocurrencies on contemporary business and economic practices.

Cryptocurrencies, digital assets utilizing cryptography for security, are primarily based on blockchain technology. Given the sector's rapid expansion and inherent dynamism, research on the cryptocurrency market is continually evolving. The literature highlights key themes such as market efficiency and price discovery (Al-Yahyaee et al. 2020; Makarov and Schoar 2019; Brauneis and Mestel 2018; Wei 2018; Lengyel-Almos and Demmler 2021), volatility and correlations (Koutmos 2018; Yi et al. 2018; Katsiampa 2019a, 2019b; Charfeddine et al. 2022; Xu et al. 2021), market microstructure (Dimpfl 2017), regulatory impacts (Zetzsche et al. 2018; Cumming et al. 2019; Chokor and Alfieri 2021; Leitch, et al. 2021), and cryptocurrency trading (Fang et al. 2022; Sebastião and Godinho 2021). In subsequent discussions on cross-asset dependency within cryptocurrencies, these references will be more thoroughly examined.

Over the past decade, there has been a growing interest in the academic community regarding the study of dependence structures among various random variables in the cryptocurrency market, as well as their connections to traditional markets. Recent studies have extensively documented the hedge and diversification properties of cryptocurrencies against traditional assets such as stocks, gold, fiat currencies, equities, and commodities, as investigated by Almeida and Gonçalves (2023). The authors concluded that cryptocurrencies exhibited time-varying and market-dependent diversification and safe-haven properties.

The literature on cross-asset dependence within the cryptocurrency market has predominantly focused on the analysis of returns and volatility. Numerous studies have examined the interdependence between the prices of Bitcoin and other cryptocurrencies utilizing autoregressive distributed lag (Ciaian and Rajcaniova 2018) and dynamical conditional correlation models (Corbet et al. 2018). Researchers have also identified timely rising return and volatility spillovers among major cryptocurrencies (Koutmos

2018; Ji et al. 2019) as well as high and periodically fluctuating volatility connectedness in the cryptocurrency market (Yi et al. 2018). Furthermore, studies have emphasized the leading role played by large-capitalization coins in transmitting volatility shocks (Ciaian and Rajcaniova 2018; Balli et al. 2020). Additionally, researchers have reported volatility co-movement in leading cryptocurrencies (Katsiampa 2019a, 2019b) and strong positive correlations among the volatilities of popular cryptocurrencies (Canh et al. 2019). Recent work has examined the volatility connectedness in the cryptocurrency market by grouping various cryptocurrencies into different categories and identifying high levels of connectedness (Charfeddine et al. 2022). Some studies have also investigated tail dependence among cryptocurrencies using methods such as the TENET approach (Xu et al. 2021) and found evidence of risk spillover effects and timely rising connectedness. Notably, all of these studies are limited to linear dependence.

Many studies have explored liquidity and risk management in the cryptocurrency market, employing liquidity measures based on either full orderbook data focusing on BTC (Makarov and Schoar 2019; Brauneis et al. 2018, 2022; Dyhrberg et al. 2018; Marshall et al. 2019; Ma et al. 2022; Scharnowski 2021) or practical estimators (Manahov 2021; Leirvik 2022; Zhang et al. 2020; Al-Yahyaee et al. 2020; Brauneis and Mestel 2018; Wei 2018; Dimpfl 2017; Brauneis et al. 2021; Theiri et al. 2022; Ghabri et al. 2021; Loi 2017; Koenraadt and Leung 2022; Saleemi 2021; Shi 2017; Dong et al. 2022; Tang and Wang 2022; Fink and Johann 2014; Moreno et al. 2022). However, the dependence structure in cryptocurrency liquidity remains less explored.

Liquidity commonality or co-movement, which refers to the linkage between a single asset's liquidity level and market liquidity, has been extensively studied in traditional markets due to its significant impact on market systemic risk; see examples by Chordia et al. (2000a); Chordia et al. (2000b); Brockman et al. (2009); Karolyi et al. (2012); Cespa and Foucault (2014). In the context of the cryptocurrency market, liquidity commonality has been examined in only a few studies. Tripathi et al. (2022) investigated liquidity commonality across a sample of 53 cryptocurrencies and concluded that the cryptocurrency market exhibited relatively high levels of liquidity commonality. Ahmed (2022) discovered that Bitcoin's liquidity was driven by various factors, including Ethereum liquidity. Anciaux et al. (2021) found strong co-movements in cryptocurrency liquidity during highly volatile regimes based on order-book data. Liquidity connectedness, which can capture both cross-asset liquidity linkages and liquidity commonality, has been investigated by Hasan et al. (2022) among six major cryptocurrencies, revealing that BTC and LTC play a significant role in determining the magnitude of connectedness.

The literature often discusses the intra-asset relationship between return and liquidity in the context of market efficiency, maturity, and price formation. Several studies have demonstrated the importance of liquidity in the cryptocurrency market. For instance, Manahov (2021) revealed that traders could drive demand liquidity even during significant price fluctuations. Dong et al. (2022) found that decreased liquidity led to higher abnormal returns but hindered market efficiency. In their evaluation of the cost of liquidity preference for portfolios combining traditional assets and cryptocurrencies, Moreno et al. (2022) demonstrated that considering liquidity made portfolios with the highest expected returns unavailable, which was similarly concluded by Ma et al. (2022). Moreover, Wei (2018) discovered that liquidity played a significant role in market efficiency, while Brauneis et al. (2022) reported that as liquidity levels increased, the cryptocurrency market became less inefficient.

Furthermore, several studies have employed copula models to examine the dependence between return and volume, a common liquidity indicator, such as Naeem et al. (2020a), Naeem et al. (2020b), Chan et al. (2022) and Yarovaya and Zięba (2022), identifying asymmetric tail dependence under different situations. Additionally, the linkages between cryptocurrency liquidity and fiat currencies have been examined by Brauneis et al. (2018, 2022), traditional financial assets by Zulfiqar and Gulzar (2021), Qarni and Gulzar (2021), Scharnowski (2021), Ghabri et al. (2021) and Loi (2017), and social events by Brauneis et al. (2021), Koenraadt and Leung (2022) and Saleemi (2021).

Data and variables

The six major cryptocurrencies of BTC, ETH, XRP, BNB, LTC, and DOGE are selected in this study, considering their high market capitalization, data availability, and diverse use cases. BTC,[2] the first and largest cryptocurrency, is the most studied cryptocurrency; see recent reviews by Lengyel-Almos and Demmler (2021), Manimuthu et al. (2019), and Kayal and Rohilla (2021). ETH[3] is the second largest cryptocurrency; its platform supports smart contracts and decentralized applications, making it an integral and central part of the blockchain ecosystem (Tripathi et al. 2022). XRP,[4] developed by Ripple Labs, aims to enable efficient cross-border transactions. BNB,[5] the native coin of the world's biggest centralized cryptocurrency exchange, has gained prominence due to its utility within the trading platform. LTC,[6] an early alternative to Bitcoin, is known as "the silver to Bitcoin's gold" because of its faster transaction time and lower gas fees. It is also among the most accepted digital assets by merchants globally. DOGE,[7] initially created as a joke, has become popular due to its strong community support and internet meme culture.

All the data used in this study were collected from the Coinmarketcap website in US dollar units and covered a 1000-day period from March 06, 2020, to November 30, 2022. This time frame was selected to capture the market dynamics during a period marked by significant fluctuations, including the COVID-19 pandemic's impact on the global economy and growing mainstream adoption of cryptocurrencies. By selecting the six major cryptocurrencies with substantial market capitalization, this study addresses a significant portion of the overall cryptocurrency market and is of interest to investors, traders, and regulators.

The daily log returns of each cryptocurrency are computed as follows:

$$r_t = \ln\left(C_t/C_{t-1}\right), \tag{1}$$

[2] https://bitcoin.org

[3] https://ethereum.org

[4] https://xrpl.org

[5] https://bnbchain.org

[6] https://litecoin.org

[7] https://dogecoin.com

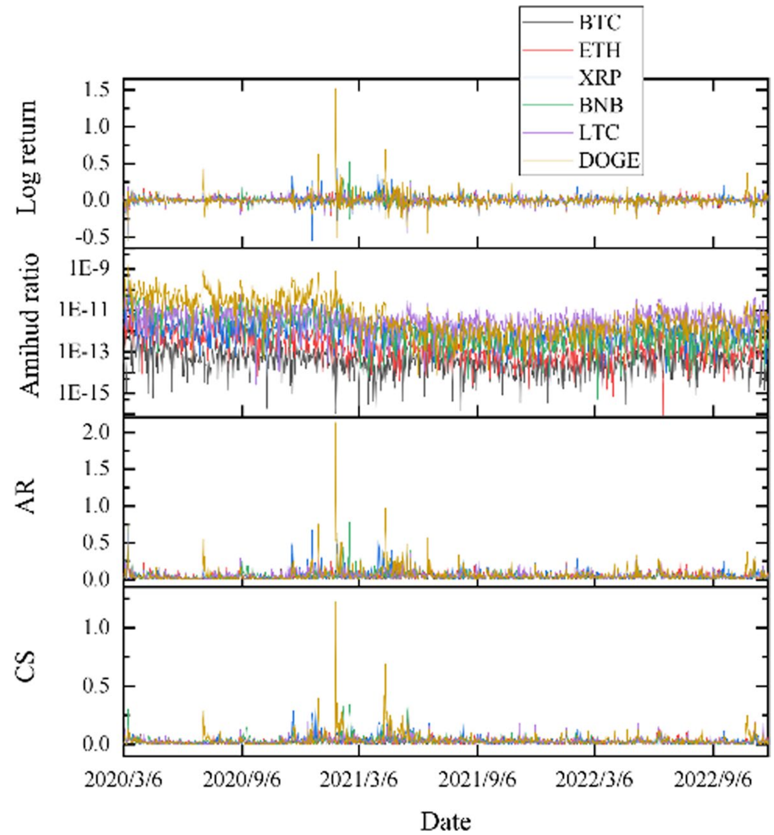


Fig. 1 This figure shows the calculated daily log returns and three liquidity proxies for six cryptocurrencies: BTC, ETH, XRP, BNB, LTC and DOGE

where C_t and C_{t-1} represent the closing prices of each asset on days t and t − 1, respectively. The first row in Fig. 1 displays the log returns for the selected six cryptocurrencies, while Table 1a lists the statistical descriptions of these log returns. The data exhibit negative skewness (except for DOGE) and significant excess kurtosis, while the Jarque–Bera (JB) test statistic (Mantalos 2011) indicates that none of the series is unconditionally normal.

The three liquidity proxies are calculated from the daily open, high, low, and close (OHLC) data in the following.

The ***Amihud*** ratio is defined as follows:

$$Amihud_t = \frac{|C_t/O_{t-1}|}{V_t}, \tag{2}$$

where O_t and V_t are the open prince and trading volume on day t, respectively. This ratio is widely used in the literature as a proxy for liquidity. However, Brauneis et al. (2021) discovered that the Amihud ratio did not capture the time variation of the BAS well, where the latter represented the costs of immediately trading an asset. Tables 1b shows the statistical descriptions of the Amihud ratio data for the selected six cryptocurrencies. We note that the Amihud ratios have very small absolute values spreading several orders of magnitude (on the order of 10^{-16}–10^{-11}) due to the large and rapidly increasing

Table 1 Statistical description of log return, Amihud ratio, AR estimator and CS estimator

	Mean	Median	Min	Max	SD	Skewness	Kurtosis	JB test
(a) The log return								
BTC	0.000637	0.001259	− 0.464730	0.171821	0.039969	− 1.645013	22.786427	16,763.623431
ETH	0.001732	0.003318	− 0.550732	0.230695	0.052864	− 1.391422	17.247584	8780.744581
XRP	0.000534	0.001493	− 0.550504	0.444758	0.064547	− 0.158011	16.861647	8010.213652
BNB	0.002671	0.001669	− 0.543084	0.529218	0.057645	− 0.277035	22.385579	15,671.153220
LTC	0.000245	0.001895	− 0.449062	0.248434	0.054952	− 1.229674	12.929899	4360.470073
DOGE	0.003753	− 0.000359	− 0.515112	1.516382	0.091526	5.321991	85.325980	287,119.222238
	Mean $\times 10^{-14}$	**Median $\times 10^{-14}$**	**Min $\times 10^{-14}$**	**Max $\times 10^{-14}$**	**SD $\times 10^{-14}$**	**Skewness**	**Kurtosis**	**JB test**
(b) The Amihud ratio								
BTC	7.0477	3.4448	0.0104	409.5265	16.8718	15.2011	334.6116	4,620,439.6960
ETH	47.3920	15.0680	0.8997	3421.3469	145.0457	14.7263	307.5153	3,899,877.2974
XRP	194.0525	109.7708	0.2210	5382.6278	322.1349	7.3743	90.9527	331,382.8811
BNB	415.1032	76.7865	0.0528	28,067.5024	1216.0208	13.5735	278.8789	3,201,921.4240
LTC	653.8813	387.6598	0.2240	18,186.5536	950.3002	8.0781	125.7045	638,225.6223
DOGE	2920.2905	317.8923	0.7279	155,645.8491	8893.1952	8.5539	111.6264	503,849.0474
	Mean	**Median**	**Min**	**Max**	**SD**	**Skewness**	**Kurtosis**	**JB test**
(c) The AR estimator								
BTC	0.039367	0.026833	0.000132	0.632451	0.041421	4.326497	47.587180	85,953.787349
ETH	0.052990	0.037975	0.000607	0.767455	0.052553	3.891073	39.590937	58,310.769351
XRP	0.055270	0.035045	0.000085	0.677113	0.069309	3.843089	24.082264	20,980.800416
BNB	0.051938	0.034234	0.000206	0.783236	0.061424	4.925506	45.417644	79,012.456082
LTC	0.05399	0.036392	0.000368	0.628165	0.053793	3.081637	21.741254	16,217.523303
DOGE	0.061771	0.033178	0.000251	2.128672	0.107747	9.136417	147.063547	878,675.086570
(d) The CS estimator								
BTC	0.021672	0.015686	0.000055	0.152749	0.020790	2.113003	9.105954	2297.575119
ETH	0.029825	0.022333	0.000072	0.269521	0.026741	2.318779	13.577177	5557.650956
XRP	0.032057	0.021080	0.000010	0.315072	0.035755	3.126842	17.179436	10,006.873453
BNB	0.030626	0.021413	0.000097	0.346494	0.034948	4.310991	31.257624	36,367.994240
LTC	0.030836	0.023615	0.000018	0.207891	0.028535	2.325228	10.664263	3348.652811
DOGE	0.037843	0.021958	0.0	1.225102	0.062157	9.445584	151.245104	930,561.967656

trading volume in the crypto market (see Eq. (2)). This causes numerical instabilities in subsequent modeling; thus, the logarithmic value, $\log_{10} \text{Amihud}_t$, will be used for further analyses instead of the original one.

The ***AR*** estimator is derived from the natural logarithms of high (H_t), low (L_t), and closing (C_t) prices, i.e., $h_t = \ln(H_t)$, $l_t = \ln(L_t)$, and $c_t = \ln(C_t)$. It is defined as follows:

$$AR_t = \sqrt{\max\{4(c_t - p_t)(c_t - p_{t+1}), 0\}}, \tag{3}$$

with $p_t = (h_t + l_t)/2$. The descriptive statistics for the AR estimator for the six cryptocurrencies are shown in Table 1d.

The ***CS*** estimator is computed from the high and low prices of two adjacent days as follows:

$$CS_{t,t+1} = \frac{2[\exp(\alpha) - 1]}{1 + \exp(\alpha)}, \tag{4}$$

where $\alpha = \frac{\sqrt{2b}-\sqrt{b}}{3-2\sqrt{2}} - \sqrt{\frac{c}{3-2\sqrt{2}}}$, with $b = \left[\ln\left(H_t/L_t\right)^2 + \ln\left(H_{t+1}/L_{t+1}\right)\right]^2$ and $c = [\ln(H_{t,t+1}/L_{t,t+1})]^2$. Here, $H_t(L_t)$ is the daily high (low) price and $H_{t,t+1}$ $(L_{t,t+1})$ is the highest (lowest) price within two adjacent days. The descriptive statistics for the CS estimator for the six cryptocurrencies are presented in Table 1c.

It is important to note that all three of these indicators are measures of illiquidity, rather than direct measures of liquidity. The Amihud ratio measures the price impact of asset sales, while both the CS and AR estimators are commonly used as proxies for the effective BAS. A higher BAS indicates higher costs associated with selling assets in the market. According to Gao et al. (2019), the AR estimator outperforms the CS estimator when the ratio of return volatility to BAS is small, and vice versa. The daily liquidity measures calculated using these indicators are shown in Fig. 1, with corresponding statistics presented in Table 3. All three liquidity indicators exhibit significant skewness and excess kurtosis, and the JB tests indicate non-normality in all the sample data.

Methodologies

To examine the cross-asset dependency structure in return and liquidity among the cryptocurrencies as well as the intra-asset return-liquidity relationship, copula-based models are used. It should be noted that copulae are primarily applicable to stationary time series (Sadegh et al. 2017). Autocorrelated time series can produce spurious dependencies between sets of variables, leading to inaccurate copula-dependency structures (Tootoonchi et al. 2020). Therefore, a pre-processing step is necessary to ensure both mean and variance stationarity within the time series. To address mean stationarity, the ARIMA model (Shumway and Stoffer 2017) can be used to eliminate nonstationarity in the mean (i.e., the trend). Additionally, the GARCH model can be applied to remove variance autocorrelations present in the residuals obtained from the ARIMA model. Thus, the resulting time series of standardized residuals can meet the stationarity requirements of copula models.

Stationary test

The fundamental concept of stationarity in a time series implies that the data distribution remains independent of time t, indicating that knowledge of time alone does not provide any information about the distribution. To assess the stationarity of both return and liquidity data, as well as to detect any potential ARCH effects, several well-established statistical tests have been employed. These include the Ljung–Box (LB) Q-test (Ljung and Box 1978) for autocorrelations, Engle LM test (Engle 1982) for ARCH effects, and augmented Dickey–Fuller (ADF) (Dickey and Fuller 1981) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests (Kwiatkowski et al. 1992) for unit roots. These tests ensure a comprehensive assessment of the stationarity characteristics within the time series data under investigation.

ARIMA models

The ARIMA (p, g, q) model addresses the presence of mean non-stationarity in a time series by representing the series data, d_t, by the following equation:

$$d_t^{(g)} = \epsilon_t + \mu + \sum_{i=1}^{p} \alpha_i d_{t-i}^{(g)} + \sum_{j=1}^{q} b_j \epsilon_{t-j}, \tag{5}$$

where μ is a constant, $d_t^{(g)}$ represents the differencing transformation of d_t of order g, a_i denotes the parameters of the autoregressive (AR) component, b_i signifies the parameters of the moving average (MA) component, and ϵ_t corresponds to the residuals. The orders, p and q, can be determined by examining the Akaike information criterion (AIC), which is associated with the likelihood, L, of the data as follows:

$$AIC = 2k - \ln(L), \tag{6}$$

where $k = p + q + 1$ represents the number of parameters. The model exhibiting the smallest AIC value is typically selected to describe the data's mean stationarity, ensuring an appropriate balance between model complexity and goodness of fit.

GARCH-type models

Bollerslev (1986) introduced the standard GARCH (SGARCH) model as a more parsimonious alternative to the original ARCH volatility model developed by Engle (1982). Consequently, the SGARCH approach utilizes fewer parameters, reducing the computational burden. Since its inception, various GARCH-type models (Zivot 2009) have been developed to estimate and forecast the volatility of a time series, effectively capturing phenomena such as volatility clustering and heteroscedasticity. In this study, we consider four distinct variations of GARCH models: SGARCH, exponential GARCH (EGARCH), asymmetric power ARCH (APARCH), and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH). Each of these models employs unique dynamical equations to describe volatility, accounting for specific characteristics present within time series data.

Standard GARCH

Assuming the residual of a time series ϵ_t in Eq. (5) follows a specific probability density function with a zero mean and a conditional variance σ^2, a SGARCH (p, q) model can be expressed as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2. \tag{7}$$

In this equation, ω represents a constant term, while α_i and β_i denote the ARCH and GARCH parameters, respectively. The pair (q, p) indicates the number of auto- correlation terms, and in this study, we focus on $(q, p) = (1, 1)$, defining $\alpha_1 \equiv \alpha$ and $\beta_1 \equiv \beta$. To ensure a stationary process and the positivity of the conditional variance, the SGARCH model imposes the conditions $\omega, \alpha, \beta \geq 0$ and $\alpha + \beta < 1$. However, if $\alpha + \beta = 1$, the SGARCH model converges to the integrated GARCH (IGARCH) model.

EGARCH

The EGARCH model accounts for the asymmetric impacts of positive and negative shocks on volatility. The dynamics of the conditional variance in an EGARCH (1, 1) model are represented as follows:

$$\ln\left(\sigma_t^2\right) = \omega + \alpha\left(\frac{|\in_t - 1|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right) + \beta \ln\left(\sigma_{t-1}^2\right) + \gamma \frac{\in_{t-1}}{\sigma_{t-1}}. \tag{8}$$

In this equation, the parameter, β, denotes the persistent effect, while α and γ capture the size and sign effects of return shocks on volatility. Unlike the SGARCH and IGARCH models, the EGARCH model does not impose restrictions on these parameters.

APARCH

The APARCH model introduces an additional power parameter, δ, to account for the observation that sample autocorrelations of returns are typically larger than those of squared returns. The dynamics of volatility in the APARCH model are expressed as follows:

$$\sigma_t^\delta = \omega + \alpha(|\in_t - 1| - \gamma \in_{t-1})^\delta + \beta\sigma_{t-1}^\delta. \tag{9}$$

The APARCH model requires $\omega, \alpha, \beta, \delta \geq 0$ and $-1 \leq \gamma \leq 1$. When $\delta = 1$, the APARCH model reduces to the threshold ARCH (TARCH) model.

GJR-GARCH

The GJR-GARCH model captures the leverage effect through the following volatility dynamics:

$$\sigma_t^2 = \omega + (\alpha + \gamma \mathrm{I}_{t-1}) \in_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{10}$$

where $\mathrm{I}_{t-1} = 1$ if $\epsilon_{t-1} < 0$ and $\mathrm{I}_{t-1} = 0$ if $\epsilon_{t-1} \geq 0$. The parameter restrictions for the GJR-GARCH model are similar to those of the SGARCH model.

Copula-based Model

Copula functions enable the separation of marginal distributions from the dependence structure of a given multivariate distribution. Let F represent a d-variate continuous distribution function with marginal distribution functions, F_p, for $p \in 1, \ldots, d$. According to Sklar's theorem (Sklar 1959), F can be decomposed as follows:

$$F(\chi) = C(F_1(x_1), \ldots, F_d(x_d)), \quad \chi = (x_1, \ldots, x_d) \in R^d, \tag{11}$$

where C is the unique copula associated with F. The copula density and density of the multivariate distribution are given by

$$
\begin{aligned}
c(u_1,\ldots,u_d) &= \frac{\partial^d C(u_1,\ldots,u_d)}{\partial u_1,\ldots,\partial u_d}, u_1,\ldots,u_d \in [0,1],\\
f(x_1,\ldots,x_d) &= c(F_1(x_1),\ldots,F_d(x_d))\prod_{i=1}^{d} f_i(x_i).
\end{aligned}
\tag{12}
$$

A key advantage of this approach is that the marginal distributions need not be similar in any way, and the choice of copula is not constrained by the selection of marginal distributions. By definition, C is a d-variate distribution function on the unit cube $[0, 1]^d$, with univariate marginals being standard uniform distributions on the interval [0, 1]. In practice, a bivariate copula typically models a pair of random variables reasonably well. However, when dealing with higher dimensions, copula models become increasingly rigid and often fail to provide valuable information. To address this issue, regular vine (R-vine) copulae have been developed to decompose the high-dimensional copula density into combinations of bivariate copulae using conditional probabilities (Joe 1996; Bedford and Cooke 2002). The mathematical form of the copula density in an R-vine is as follows:

$$
c(u_1,\ldots,u_d) = \prod_{u\in E(V)} c_{u|D_u}\left(F_{u_j|D_u}, F_{u_k|D_u}\right),
\tag{13}
$$

where $\mathbf{u} = (u_j, u_k)$ are edges in the R-vine with $j \neq k \in \{1, 2,\ldots, d\}$, $D_\mathbf{u}$ represents conditional constraints depending on variables other than u_j and u_k, $F_{u_{j(k)}|D_u}$ denotes the conditional probabilities, and $c_{u|D_u}$ corresponds to bivariate copula densities.

In this study, we apply R-vine copula models to investigate the dependencies among liquidity measures of cryptocurrencies, as well as the dependence between liquidity and returns. To achieve this objective, we utilize empirical cumulative distribution functions derived from standardized residuals of GARCH-type models, which are subsequently fitted to R-vine models using parametric bivariate copulae, as described in reference Dissmann et al. (2013). The R-vine trees are constructed employing a maximum-spanning tree algorithm based on the empirical Kendall's τ measure. Moreover, the selection of the bivariate copula characterizing the dependency between connected tree nodes is conducted using the AIC in Eq. (6).

We consider two types of dependency measures in this study. One measure is the tail dependence, which describes the probability that a random variable, u_1, exceeds a certain threshold given that another random variable has already exceeded the same threshold. The tail dependence can be both lower- and upper-tail dependence, which are defined using the copula as follows (Joe et al. 2010):

$$
\begin{aligned}
\lambda_L &= \lim_{\nu\to 0} \frac{C(\nu,\nu)}{\nu},\\
\lambda_U &= \lim_{\nu\to 1} \frac{1-2\nu+C(\nu,\nu)}{1-\nu}.
\end{aligned}
\tag{14}
$$

Another dependence measure is Kendall's τ coefficient, employed to quantify the order correlation between two random variables, u_1 and u_2. As defined by Schweizer and Wolff (1981), this dependence measure is expressed as follows:

$$\tau = 4\iint C\left(u_1,u_2\right)dC\left(u_1,u_2\right) - 1 = 4\mathbb{E}\left[C\left(u_1,u_2\right)\right] - 1, \tag{15}$$

which depends solely on copula functions, and thus on the parameters defining the functional form of $C\left(u_1,u_2\right)$.

The selection set for bivariate copula functions in this study includes Elliptical copulae (Gaussian copula, Student's T copula), Archimedean copulae (Independence, Clayton, Gumbel, Frank, Joe, and BB family copulae), and their modified versions with rotation angles of 90°, 180°, or 270° (Czado 2019). Elliptical copulae differ from Archimedean copulae in that they possess only implicit analytical expressions, and they generally exhibit a greater ability to express more complex dependency structures. Archimedean copulae can capture a wide range of dependencies and can be represented by a generator function, ψ, satisfying the following expression (McNeil and Nešlehová 2009):

$$C\left(u_1,u_2\right) = \Psi^{-1}(\Psi(u_1) + \Psi(u_2)). \tag{16}$$

A summary of the Elliptical and Archimedean copulae, along with their corresponding Kendall's τ and tail dependence coefficients, is presented in Table 2. It can be observed that the Clayton copula is suitable for describing lower-tail dependence, while upper-tail dependence may be captured by the Gumbel, Joe, and BB6 copulae. Furthermore, the Student's T copula exhibits symmetrical dependence, while the BB1 and BB7 copulae display asymmetrical lower-tail and upper-tail dependence. Last, the Frank, BB8, and Gaussian copulae possess symmetrical lower- and upper-tail independence.

Results and discussions

Data pre-processing

Statistical tests

Table 3 presents the results of various statistical tests conducted on the data. To improve the stability of numerical calculations, we have rescaled the data by a factor of 1 for the log Amihud ratio and 10^3 for the rest. This factor will be employed for all calculations throughout the remainder of the study.

For the log returns in Table 3a, the LB Q-tests, $Q(10)$, with an order of 10 reject the null hypothesis for all six cryptocurrencies except for the log-return series of XRP. This finding suggests significant serial correlations in the log returns of the other five cryptocurrencies. The same tests on the squared log returns [$Q^2(10)$] indicate a necessity for volatility modeling, considering the existing autocorrelations in the squared-return series. This is further substantiated by the Engle LM test statistics [ARCH(10) in Table 3a], which demonstrate the presence of the ARCH effect in all the log return data. The stationarity of the log-return series is examined using the ADF and KPSS tests. While the ADF results strongly suggest that the return data for all six cryptocurrencies are stationary, the KPSS test indicates non-stationarity for BTC and ETH. This situation implies the existence of some trends in the log-return series of BTC and ETH, although the log of returns is utilized.

The same types of statistical tests were applied to the time series of the log Amihud ratio, AR, and CS estimators, with the results presented in Table 3b–d, respectively. The LB Q-test indicates that serial correlations are present in the time series of all

Table 2 Selected copula models and their features. B is the beta function

Symbol	Elliptical	Parameter range	Kendall's τ	Tail dependence
E1	Gaussian	$\theta \in (-1,1)$	$\frac{2}{\pi} arc \sin\theta$	0
E2	Student's T	$\theta \in (-1,1), \nu > 2$	$\frac{2}{\pi} arc \sin\theta$	$2t_{\nu+1}\left(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}}\right)$

Symbol	Archimedean	Generator function Ψ	Parameter range	Kendall's τ	Tail dependence (lower, upper)
A1	Independence	$-\log t$	NA	NA	NA
A2	Clayton	$\frac{1}{\theta}\left(t^{-\theta}-1\right)$	$\theta > 0$	$\frac{\theta}{\theta+2}$	$\left(2^{-\frac{1}{\theta}},0\right)$
A3	Gumbel	$(-\log t)^{\theta}$	$\theta \geq 1$	$1-\frac{1}{\theta}$	$\left(0,2-2^{\frac{1}{\theta}}\right)$
A4	Frank	$-\log\left(\frac{\exp(-\theta t)-1}{\exp(-\theta)-1}\right)$	$\theta \in R$	$1-\frac{4[1-D_1(\theta)]}{\theta}, D_1(\theta)=\frac{1}{\theta}\int_0^{\theta}\frac{t}{e^t-1}dt$	$(0,0)$
A5	Joe	$-\log\left(1-(1-t)^{\theta}\right)$	$\theta \geq 1$	$1+\frac{4}{\theta^2}\int_0^1 t\log(t)(1-t)^{\frac{2(t-\theta)}{\theta}}dt$	$\left(0,2-2^{\frac{1}{\theta}}\right)$
A6	BB1	$(t^{-\theta}-1)^{\delta}$	$\theta > 0, \delta \geq 1$	$1-\frac{2}{\delta(\theta+2)}$	$\left(2^{-1/(\theta\delta)},2-2^{1/\delta}\right)$
A7	BB6	$\left(-\log\left[1-(1-t)^{\theta}\right]\right)^{\delta}$	$\theta \geq 1, \delta \geq 1$	$1+4\int_0^1\left[-\log\left(1-t^{\theta}\right)\frac{t-t^{1-\theta}}{\theta\delta}\right]dt$	$(0,2-2^{1/(\theta\delta)}$
A8	BB7	$[1-(1-t)^{\theta}]^{-\delta}-1$	$\theta \geq 1, \delta > 0$	$1-\frac{2}{\delta(2-\theta)}+\frac{4}{\theta^2\delta}B\left(\frac{2-\theta}{\theta},\delta+2\right)$	$2^{-1/\delta},2-2^{1/\theta}$
A9	BB8	$-\log\left[\frac{1-(1-\delta t)^{\theta}}{1-(1-\delta)^{\theta}}\right]$	$\theta \geq 1, 0 < \delta \leq 1$	$1+4\int_{1-\delta}^1\left[\log\left(\frac{(1-\delta)^{\theta}-1}{t^{\theta}-1}\right)\frac{t-t^{1-\theta}}{\theta\delta^2}\right]dt$	$(0,0)$

Table 3 Various test statistics for all the data

	Q(10)	Q^2(10)	ARCH(10)	ADF	KPSS
(a) The log return series					
BTC	21.66**	18.65**	87.90***	− 33.65***	0.53**
ETH	30.60***	31.90***	65.74***	− 9.70***	0.43*
XRP	7.74	64.89***	56.58***	− 32.77***	0.12
BNB	46.07***	114.55***	142.58***	− 8.59***	0.31
LTC	22.87**	67.81***	69.30***	− 33.82***	0.15
DOGE	39.57***	25.19***	21.91**	− 16.69***	0.28
(b) The log Amihud ratio series					
BTC	259.51***	232.88***	99.2***	− 3.73***	2.33***
ETH	1902.32***	1777.51***	361.87***	− 3.41**	3.74***
XRP	385.37***	357.92***	130.78***	− 5.59***	1.92***
BNB	3144.45***	2924.21***	486.86***	− 2.57*	4.28***
LTC	209.73***	186.08***	81.56***	− 4.43***	0.93***
DOGE	3961.36***	3754.68***	568.39***	− 38.19***	3.59***
(c) The AR estimator series					
BTC	107.82***	27.52***	69.25***	− 5.12***	0.23
ETH	99.52***	30.35***	62.78***	− 10.12***	0.17
XRP	278.77***	88.78***	76.46***	− 6.20***	0.41*
BNB	287.98***	81.41***	85.97***	− 4.77***	0.51**
LTC	100.12 ***	40.01***	54.17***	− 5.71***	0.31
DOGE	348.06***	20.81**	18.63**	− 6.57***	0.32
(d) The CS estimator series					
BTC	277.21***	184.83***	132.77***	− 9.09***	0.30
ETH	289.48***	212.17***	195.18***	− 9.09***	0.24
XRP	624.73***	354.91***	192.88***	− 5.35***	0.65**
BNB	462.59***	342.7***	348.61***	− 6.90***	0.61**
LTC	208.89***	73.35***	51.49***	− 9.32***	0.43*
DOGE	511.85***	25.56***	22.12**	− 6.74***	0.28

*Indicate rejection of the respective null hypotheses at the 10% significance level

**Indicate rejection of the respective null hypotheses at the 5% significance level

***Indicate rejection of the respective null hypotheses at the 1% significance level

three liquidity measures and their squared series. The Engle LM test reveals that the ARCH effect is also significant in all the data. The combination of the ADF and KPSS test statistics demonstrates that trends are present in all the log-Amihud-ratio series, but only in some of the AR and CS estimator series, as indicated by both the rejected ADF and KPSS null hypotheses. Stationarity is confirmed for the remaining data, as the ADF null hypothesis is rejected and the KPSS null hypothesis is accepted.

ARIMA modeling

The presence of potential trends in the time-series data of both return and liquidity measures (refer to Table 3) necessitates the utilization of ARIMA models prior to implementing GARCH-type models. We fit both the return and liquidity data to the model in Eq. (5) using the maximum likelihood estimation (MLE) method, selecting the order parameters (p, d, q) based on the AIC in Eq. (6) with the constraints of $0 \leq p, q \leq 15$ and $0 \leq d \leq 2$. The results are presented in Table 4, accompanied by the LB Q-test ($Q(10)$),

Table 4 Fitting results of the ARIMA model and statistics of residual tests

	(*p*, *d*, *q*)	AIC	Q(10)	$Q^2(10)$	ARCH(10)	ADF	KPSS
(a) Log return							
BTC	(0, 0, 4)	10,211.5	8.73	14.94	76.30***	− 31.59***	0.49*
ETH	(2, 0, 6)	10,767.2	6.85	20.93**	43.80***	− 31.77***	0.36*
XRP	(0, 0, 0)	11,173.7	7.74	64.89***	56.58***	− 32.77***	0.12
BNB	(2, 0, 2)	10,933.0	15.67	98.08***	123.77***	− 8.98***	0.28
LTC	(1, 0, 4)	10,845.8	4.35	45.76***	49.56***	− 31.60***	0.15
DOGE	(3, 0, 3)	11,857.4	2.92	13.17	11.99	− 31.60***	0.25
(b) Log Amihud ratio							
BTC	(4, 1, 5)	1648.2	12.41	0.78	7.77	− 40.68***	0.43*
ETH	(0, 1, 1)	1446.4	5.12	0.35	5.36	− 38.72***	0.58**
XRP	(2, 1, 5)	1533.3	3.60	0.16	8.54	− 39.03***	0.35*
BNB	(0, 1, 1)	1632.7	3.32	0.16	4.46	− 37.32***	0.32
LTC	(0, 1, 1)	1597.2	5.96	0.21	6.25	− 23.70***	0.93***
DOGE	(2, 1, 1)	1668.6	9.15	0.37	10.52	− 38.19***	0.36*
(c) AR estimator							
BTC	(5, 1, 7)	10,207.8	4.07	4.15	12.46	− 31.34***	0.08
ETH	(2, 1, 3)	10,705.7	3.18	12.17	33.00***	− 15.37***	0.12
XRP	(3, 1, 9)	11,175.8	2.47	27.28***	32.05***	− 31.40***	0.09
BNB	(3, 1, 3)	10,928.4	7.32	37.72***	60.25***	− 30.89***	0.04
LTC	(6, 1, 3)	10,745.7	2.15	26.98***	34.71***	− 31.55***	0.09
DOGE	(7, 1, 8)	12,023.8	3.07	0.74	0.72	− 31.87***	0.04
(d) CS estimator							
BTC	(1, 1, 1)	8765.0	6.50	63.36***	62.72***	− 31.61***	0.05
ETH	(0, 1, 2)	9239.1	6.85	143.15***	145.29***	− 31.43***	0.04
XRP	(0, 1, 9)	9724.8	1.37	146.89***	97.22***	− 31.38***	0.08
BNB	(6, 1, 4)	9705.3	6.75	310.38***	299.31***	− 31.68***	0.07
LTC	(1, 1, 1)	9424.4	7.75	15.63	11.68	− 31.61***	0.06
DOGE	(7, 1, 8)	10,848.8	4.58	0.97	0.94	− 31.43***	0.05

*Indicate rejection of the respective null hypotheses at the 10% significance level

**Indicate rejection of the respective null hypotheses at the 5% significance level

***Indicate rejection of the respective null hypotheses at the 1% significance level

squared LB Q-test ($Q^2(10)$), Engle LM test (ARCH(10)), ADF, and KPSS test statistics on the residuals obtained from ARIMA.

Regarding the log returns in Table 4a, no differencing ($d=0$) is required for all six cryptocurrencies. Higher orders are necessary for the AR and MA terms to describe the BNB log returns, indicating stronger serial correlations. Residuals from the ARIMA model exhibit considerably smaller LB Q-test statistics than the original data (see Table 3a) for all cryptocurrencies except XRP. The optimal ARIMA model for XRP has $(p, d, q)=(0, 0, 0)$, suggesting negligible AR and MA effects in XRP log returns. The statistics of the remaining tests [LB Q-test on squared log returns $Q^2(10)$, Engle LM test ARCH(10), ADF, and KPSS tests] for other cryptocurrencies closely resemble those of the original data in Table 3a. Considering these, we use the residuals of the ARIMA model for BTC, ETH, BNB, LTC, and DOGE in the GARCH modeling, while the original log returns will be used for XRP.

With respect to the three liquidity proxies, a first-order differencing ($d=1$) is necessary in all cases based on the obtained ARIMA models, as observed in Table 4b–d for the log Amihud ratio, AR estimator, and CS estimator, respectively. The modeling performance is generally satisfactory, as evidenced by comparing the results of the statistical tests on the ARIMA residuals to those on the original data in Table 3b–d. The null hypothesis of the LB Q-test is accepted for all the obtained residuals from the ARIMA modeling, indicating negligible serial correlations. The $Q^2(10)$ and ARCH(10) tests are also passed for all residuals of the log Amihud ratio, suggesting variance stationarity. This is consistent with the results of the ADF tests; however, some KPSS tests still indicate the contrary, particularly for the LTC coin. The $Q^2(10)$ and ARCH(10) statistics for the residuals of the AR and CS estimators imply a smaller time-dependent variance effect in DOGE than in the other five cryptocurrencies. Both ADF and KPSS tests indicate stationarity in the residuals of the AR and CS proxies across the six cryptocurrencies.

GARCH modeling

The $Q^2(10)$ and ARCH(10) statistics on the ARIMA residuals in Table 4 signify the necessity for variance modeling for the residuals of the log returns, AR, and CS estimators from the ARIMA models, but not the log Amihud ratio. Nonetheless, variance modeling will be conducted for all the ARIMA residuals in this section, employing the GARCH-type models introduced in Section "GARCH-type models". The model parameters are obtained by fitting either the original data (log returns of XRP) or the residuals of the optimal ARIMA model (the rest) to a specific GARCH-type model, along with an error distribution using the MLE method. The optimal volatility model, selected from the set of SGARCH, EGARCH, TARCH, APARCH, and GJR-GARCH, combined with the error distribution from the Gaussian, Student's T, Skewed T, and generalized error distributions (Feng and Shi 2017), is chosen based on the fitted AIC [see Eq. (6)]. The resulting standardized residuals from the GARCH-type models are then tested using various statistical tests (see Section "Stationary test").

The final results are presented in Table 5 for both the log returns and log Amihud ratio, and in Table 6 for the AR and CS estimators, respectively. The numbers in brackets indicate the standard errors of the fitted parameters. Table 5a shows that the optimal models for the log returns are either symmetric, or asymmetric with very small leverage parameters, γ. The autoregressive (α) and persistent (β) effects are significant in the return variance. The error distributions show that only the BNB log-return residuals exhibit a slightly asymmetric distribution ($\lambda \neq 0$ in Table 5a), while other return residuals are symmetrically distributed. The fitted degree of freedom, η, ranges from 3 to 5, indicating a notable fat-tail effect.

The obtained standardized residuals from the GARCH modeling of log return data pass all the $Q(10)$, $Q^2(10)$, and ARCH(10) tests, implying that both mean and variance nonstationarity are now absent. The ADF test rejects the null hypothesis of non-stationarity for all the cryptocurrency log returns, suggesting stationarity. However, the KPSS statistics in Table 3a are comparable to those of the original data, as well as to the ARIMA residuals in Table 4a.

In the case of the log Amihud ratio, the optimal models are nearly symmetric for all the cryptocurrencies except for the BNB coin. For BNB, a significant negative leverage

Table 5 Fitting results of GARCH models for the log returns and log Amihud ratio and statistics of residual tests

Opt. vol. model	BTC TARCH	ETH EGARCH	XRP EGARCH	BNB SGARCH	LTC GJR-GARCH	DOGE SGARCH
Res. dist	**Student's T**	**Student's T**	**Student's T**	**Student's T**	**Student's T**	**Student's T**
(a) Log return						
AIC	9894.1	10,504.7	10,530.3	10,383.3	10,557.2	10,663.5
μ	1.41 (0.86)	2.40 (1.28)	0.03 (1.02)	2.44 (1.08)	1.80 (1.22)	− 1.15 (0.91)
ω	0.87 (0.80)	0.78 (0.32)	0.45 (0.14)	157 (58)	89 (61)	427 (293)
α	0.07 (0.02)	0.22 (0.05)	0.38 (0.07)	0.16 (0.04)	0.16 (0.04)	0.39 (0.11)
β	0.93 (0.03)	0.90 (0.04)	0.95 (0.02)	0.80 (0.05)	0.88 (0.04)	0.61 (0.16)
γ	− 0.0007 (0.03)	− 0.08 (0.06)	0.004 (0.03)	–	− 0.10 (0.04)	–
δ	–	–	–	–	–	–
η	3.3 (0.3)	4.3 (0.6)	2.8 (0.3)	3.7 (0.5)	3.7 (0.4)	2.8 (0.2)
λ	–	–	–	–	–	–
Q(10)	10.33	11.28	7.34	12.01	9.84	6.38
Q^2(10)	3.94	3.35	3.76	3.28	8.03	0.34
ARCH(10)	12.37	4.23	4.37	3.27	8.72	0.33
ADF	− 30.22***	− 16.15***	− 31.24***	− 17.74***	− 16.14***	− 32.15***
KPSS	0.62**	0.45*	0.24	0.39	0.21	0.23
Opt. vol. model	**BTC GJR-GARCH**	**ETH SGARCH**	**XRP SGARCH**	**BNB APARCH**	**LTC GJR-GARCH**	**DOGE SGARCH**
Res. dist	**Skew T**	**Skew T**	**Skew T**	**Skew T**	**Skew T**	**Skew T**
(b) Log Amihud ratio						
AIC	1504.3	1332.3	1444.9	1460.5	1432.7	1598.2
μ	− 0.02 (0.02)	− 0.02 (0.02)	− 0.01 (0.05)	− 0.01 (0.02)	− 0.03 (0.04)	− 0.03 (0.02)
ω	0.06 (0.01)	0.07 (0.01)	0.10 (0.15)	0.04 (0.04)	0.09 (0.03)	0.11 (0.05)
α	0.09 (0.04)	0.05 (0.03)	0.00 (0.24)	0.05 (0.04)	0.09 (0.06)	0.04 (0.05)
β	0.76 (0.04)	0.65 (0.06)	0.64 (0.75)	0.44 (0.11)	0.63 (0.10)	0.60 (0.20)
γ	− 0.09 (0.04)	–	–	− 0.39 (0.10)	− 0.07 (0.06)	–
δ	–	–	–	4.0 (1.6)	–	–
η	8.1 (1.7)	8.9 (2.3)	9.0 (5.7)	5.8 (0.9)	6.2(1.1)	7.3(1.6)
λ	− 0.41 (0.04)	− 0.42 (0.04)	− 0.37 (0.05)	− 0.51 (0.04)	− 0.43 (0.04)	− 0.30 (0.04)
Q(10)	2.78	4.09	2.05	2.15	6.81	6.23
Q^2(10)	6.39	3.77	8.22	3.38	4.09	11.05
ARCH(10)	7.06	3.93	8.35	4.16	4.37	14.39
ADF	− 32.00***	− 31.89***	− 31.97***	− 31.41***	− 21.37***	− 32.07***
KPSS	0.31	0.47**	0.22	0.23	0.26	0.30

*Indicate rejection of the respective null hypotheses at the 10% significance level

**Indicate rejection of the respective null hypotheses at the 5% significance level

***Indicate rejection of the respective null hypotheses at the 1% significance level

parameter, γ, *is* obtained with an optimal APARCH model of power $\delta = 4 \pm 1.6$ [see Eq. (9)]. This suggests that negative liquidity shocks exert smaller effects than positive ones on the liquidity variance in the Amihud ratio measure for the BNB cryptocurrency. The same observation is made with the CS estimator for the XRP, LTC, and DOGE coins in Table 6b. The fitted α values are small, while the β values are large (approaching 1), indicating a significant persistent effect but weak autoregressive one.

Table 6 Fitting results of GARCH models for the AR and CS estimators, and statistics of residual tests

	BTC	**ETH**	**XRP**	**BNB**	**LTC**	**DOGE**
Opt. vol. model	**EGARCH**	**EGARCH**	**EGARCH**	**EGARCH**	**EGARCH**	**APARCH**
Res. dist	**Skew T**	**Skew T**	**Skew T**	**Skew T**	**Skew T**	**Skew T**
(a) AR estimator						
AIC	9451.6	9948.2	10,083.4	9928.0	10,052.9	10,382.4
μ	3.32 (0.08)	4.36 (0.06)	1.67 (0.04)	7.78 (0.14)	4.06 (0.03)	− 1.53 (4.35)
ω	0.05 (1E−4)	0.04 (1E−4)	0.015 (4E−5)	0.12 (3E−5)	0.04 (5E−5)	0.96 (5.39)
α	− 0.02 (6E−4)	− 0.01 (5E−4)	− 0.0183 (0.0002)	− 0.02 (6E−4)	− 0.02 (6E−4)	0.05 (0.02)
β	0.99 (3E−6)	1.00 (1E−6)	0.998 (6E−8)	0.99 (9E−7)	0.99 (1E−7)	0.95 (0.06)
γ	0.21 (6E−3)	0.17 (1E−3)	0.136 (0.005)	0.27 (4E−3)	0.15 (2E−3)	− 1.00 (0.01)
δ	–	–	–	–	–	1.2 (1.0)
η	2.44 (0.06)	2.59 (0.03)	2.35 (0.03)	2.41 (0.02)	3.45 (0.05)	3.1 (0.5)
λ	0.77 (0.07)	0.78 (0.02)	0.68 (0.03)	0.75 (0.02)	0.68 (0.02)	0.59 (0.10)
Q(10)	6.63	6.62	9.99	9.27	7.39	6.94
Q^2(10)	3.06	5.87	45.83***	4.49	13.93	0.24
ARCH(10)	4.68	10.11	51.09***	5.50	17.40*	0.24
ADF	− 31.18***	− 15.59***	− 20.52***	− 17.46***	− 21.08***	− 31.02***
KPSS	0.06	0.07	0.10	0.06	0.09	0.05
(b) CS estimator						
AIC	8237.2	8849.5	8905.1	8815.3	8811.5	9229.1
μ	− 0.07 (0.50)	0.74 (0.40)	− 0.64 (0.003)	− 0.56 (0.85)	− 0.12 (0.78)	− 0.63 (0.95)
ω	0.22 (0.08)	0.12 (0.13)	0.26 (0.14)	0.12 (0.32)	0.15(0.57)	0.47(0.69)
α	0.09 (0.01)	0.05 (0.02)	0.27 (0.09)	0.11 (0.26)	0.03(0.02)	0.05(0.01)
β	0.95 (0.01)	0.95 (0.06)	0.97 (0.02)	0.98 (0.04)	0.97(0.01)	0.95(0.02)
γ	− 0.09(0.01)	− 0.98(0.18)	0.07 (0.03)	0.09 (0.02)	− 1.00 (4E−4)	− 1.00 (5E−3)
δ	–	0.51(0.57)	–	–	1.20 (0.74)	1.1 (0.25)
η	4.6 (0.5)	5.51 (0.96)	3.4 (0.4)	3.6 (0.4)	4.3 (0.50)	3.5 (0.39)
λ	0.61 (0.03)	0.55 (0.04)	0.51 (0.03)	0.49 (0.12)	0.64 (0.07)	0.51 (0.05)
Q(10)	4.03	5.34	6.80	6.50	6.00	4.97
Q^2(10)	9.89	15.62	6.69	14.89	2.19	0.57
ARCH(10)	10.23	15.39	6.97	15.14	2.09	0.55
ADF	− 31.03***	− 31.68***	− 32.80***	− 21.25***	− 21.07***	− 29.75***
KPSS	0.05	0.07	0.05	0.10	0.08	0.05

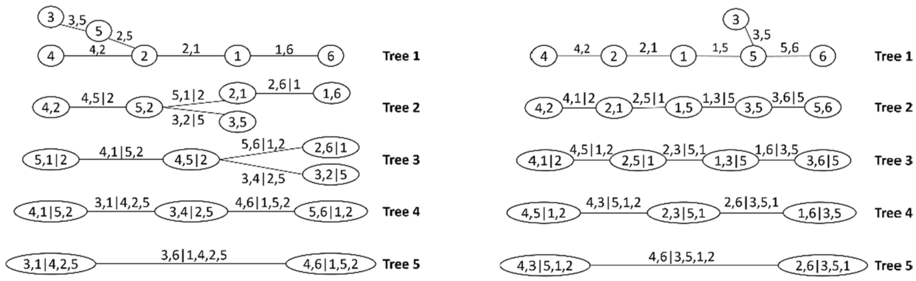
*Indicate rejection of the respective null hypotheses at the 10% significance level

**Indicate rejection of the respective null hypotheses at the 5% significance level

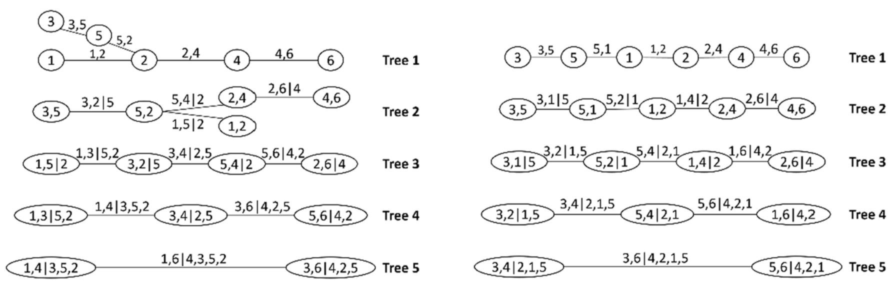
***Indicate rejection of the respective null hypotheses at the 1% significance level

The optimal residual distributions for all the six cryptocurrencies are positively skewed T distributions, with a skewness parameter, λ, approximately 4–5 and a scale parameter, η, approximately 3–6. This indicates that the residuals are distributed in an asymmetric and fat-tailed manner. Similar to the log returns, the mean and variance stationarity of the standardized residuals from GARCH for the log Amihud ratios is confirmed by the $Q(10)$, $Q^2(10)$, and ARCH(10) statistical tests. This finding is further supported by the ADF and KPSS tests, except for the KPSS statistics for the ETH coin.

The results of the AR and CS estimators in Table 6 reveal that asymmetric impacts of negative and positive liquidity shocks on liquidity variance generally exist (nonzero



(a) R-vine copula tree of the log returns (b) R-vine copula tree of the log Amihud ratio



(c) R-vine copula tree of the AR estimator (d) R-vine copula tree of the CS estimator

Fig. 2 The fitted R-vine copula trees of the log return and three liquidity proxies

γ). Two types of asymmetric GARCH models are identified: APARCH and EGARCH. When the APARCH model is selected, γ values close to -1 are observed, with the exception of the TARCH model (an APARCH model with $\delta = 1$) for the BTC CS estimator. Mild positive γ values are seen in the EGARCH model. Both situations suggest that negative liquidity shocks exert weaker effects on liquidity variance than positive ones in the crypto market. This observation may be linked to the fact that traders are more actively entering and exiting markets during less stressful periods, leading to larger liquidity variances. Conversely, during stressful market conditions, trading activities are generally suppressed. The standardized residuals from the GARCH modeling of all AR and CS data are now stationary based on the $Q(10)$, $Q^2(10)$, ARCH(10), ADF, and KPSS tests. This finding implies that the variance non-stationarity in the AR and CS data has been effectively removed by the GARCH modeling.

Copula modeling

Following the data pre-processing steps described above, the standardized residuals obtained from the GARCH modeling have become stationary and are now suitable for copula modeling. To investigate the cross-asset dependence structure of log returns and liquidity for the six cryptocurrencies, we employ the copula method outlined in Section "Copula-based model", utilizing R-vine copulae and the sequential method described by Dissmann et al. (2013). The model parameters are obtained by fitting the GARCH residual data to the copula model, and the optimal bivariate copula functions describing dependencies between adjacent nodes in the R-vine tree are chosen from the Elliptical and Archimedean families listed in Table 2 based on the smallest AIC.

Correlations among assets using R-vine copulae

In this subsection, we discuss the dependency structures of the six cryptocurrencies as revealed by our analysis of log returns and liquidity estimators using the R-vine copula method. Figure 2a–d present the obtained R-vine copula trees for the log returns, log Amihud ratio, and AR and CS estimators, respectively, where the numbers 1–6 label the BTC, ETH, XRP, BNB, LTC, and DOGE coins respectively. The R-vine structures are built by treating edges from the i-th tree as the nodes of the $(i+1)$-th tree. Nodes in the $(i+1)$-th tree are joined if the corresponding edges in the i-th tree share a node. Each edge in the i-th tree of an R-vine is labeled by $u_1, u_2|v_1, v_2, \ldots, v_{i-1}$, representing the conditional dependency between u_1 and u_2 conditioned on conditioning variables, v_1, v_2, … , v_{i-1}, i.e., the copula densities in Eq. (13). In each R-vine structure, five trees are constructed, with a total of 15 edges representing the dependencies of the 15 crypto pairs formed by the selected six cryptocurrencies. The fitted optimal copulae, as well as the corresponding Kendall's τ and tail- dependence coefficients, are listed in Table 7.

An interesting observation can be made from the dependency vine-copula tree structure of log returns displayed in Fig. 2a. ETH appears as a central node with a node degree of 3 in Tree 1 and exhibits high correlations with BTC, BNB, and LTC. This observation is further substantiated by the Kendall's τ values in Table 7. The obtained optimal bivariate copulae for the five strongly correlated crypto pairs in Tree 1 are four Gumbel (A3) and one BB6 (A7) copulae, all with a 180° rotation, which exhibit lower-tail dependence. In fact, the 180°-rotated Gumbel copula is selected as the optimal one for 8 out of the total 15 pairs. This suggests that when the market declines, these pairs are likely to fall together, whereas during bullish markets, no such correlation exists.

Weak symmetric correlations are found in other crypto pairs, where symmetric Student's T (E2) or BB8 (A9) copulae are observed in the BTC-XRP, ETH-DOGE, XRP-BNB, XRP-DOGE, BNB-LTC, and BNB-DOGE pairs. From the Kendall's τ coefficients listed in Table 7, the ETH coin has the largest mean of τ with the other five cryptos, while the DOGE coin has the smallest mean of τ. Among the selected six cryptos, ETH is the most correlated to the market, while DOGE is the least correlated.

Contrary to the vine-copula tree structure of log returns, the center node for the log-Amihud-ratio series in the first tree is LTC, as illustrated in Fig. 2b. From Table 7, it can be observed that the two most frequently selected bivariate copulae for modeling the cross-asset dependence of the log Amihud ratio in the 15 crypto pairs are the (180°-rotated) BB8 (A9) and Frank (A4) copulae. Intriguingly, both of them are used to describe nonlinear dependence in the center of the distribution with zero tail-dependence coefficients.

Strong upper-tail dependence is identified in the XRP-LTC [the Gumbel copula (A3)] and ETH-BNB [the BB6 copula (A7)] pairs, while weak symmetric tail- dependence [the Student's T copula (E2)] is observed in the BTC-XRP and XRP- BNB pairs. Noteworthily, some similarities are observed between the log-return and log-Amihud-ratio R-vine structures presented in Fig. 2a and b. For instance, strong correlations of the crypto pairs, BTC-ETH, ETH-BNB, and XRP-LTC, are found in both cases, and both R-vine structures are very close to a D-vine structure (Dissmann et al. 2013).

The R-vine-copula tree structure of the AR estimator selects ETH as the center node in Tree 1, as shown in Fig. 2c. Similar to the case of the log-Amihud-ratio, the dominant

Table 7 Copulae modeling of the log return and three liquidity proxies

Crypto pair	Log return			Log Amihud ratio			AR estimator			CS Estimator		
	Copula	τ	(lower, upper)	Copula	τ	(lower, upper)	Copula	τ	(lower, upper)	Copula	τ	(lower, upper)
BTC-ETH	A3 (180°)^{1}	0.620	(0.699, 0)	A9^{1}	0.426	(0, 0)	A9^{1}	0.391	(0, 0)	A7^{1}	0.288	(0, 0.435)
BTC-XRP	E2^{4}	0.073	(0.009, 0.009)	E2^{2}	0.128	(0.034, 0.034)	A4^{3}	0.091	(0, 0)	A9^{2}	0.101	(0, 0)
BTC-BNB	A3 (180°)^{3}	0.105	(0.141, 0)	A6 (180°)^{2}	0.126	(0.132, 5.461E−5)	A4^{4}	0.076	(0, 0)	E2^{2}	0.051	(0.022, 0.022)
BTC-LTC	A3 (180°)^{2}	0.285	(0.358, 0)	A9^{1}	0.404	(0, 0)	A9^{2}	0.197	(0, 0)	A8^{1}	0.259	(0.001, 0.430)
BTC-DOGE	A3 (180°)^{1}	0.505	(0.591, 0)	A9 (180°)^{3}	0.102	(0, 0)	A2^{5}	0.047	(0.001, 0)	A4^{3}	0.099	(0, 0)
ETH-XRP	A3 (180°)^{2}	0.174	(0.228, 0)	A4^{3}	0.112	(0, 0)	E2^{2}	0.141	(0.034, 0.034)	A3^{3}	0.055	(0, 0.074)
ETH-BNB	A7 (180°)^{1}	0.566	(0.681, 0)	A7^{1}	0.369	(0, 0.543)	A3^{1}	0.335	(0, 0.414)	A3^{1}	0.223	(0, 0.286)
ETH-LTC	A3 (180°)^{1}	0.615	(0.694, 0)	A6 (180°)^{2}	0.208	(0.129, 0.110)	A3^{1}	0.396	(0, 0.480)	A3^{2}	0.098	(0, 0.131)
ETH-DOGE	E2^{2}	0.181	(0.059, 0.059)	A4^{4}	0.131	(0, 0)	A9^{2}	0.137	(0, 0)	A3^{2}	0.110	(0, 0.147)
XRP-BNB	E2^{3}	0.115	(0.009, 0.009)	E2^{4}	0.104	(0.001, 0.001)	E1^{3}	0.099	(0, 0)	A3^{4}	0.066	(0, 0.090)
XRP-LTC	A3 (180°)^{1}	0.581	(0.663, 0)	A3^{1}	0.394	(0, 0.478)	A9^{1}	0.3087	(0, 0)	A8^{4}	0.217	(3.026E−5, 0.379)
XRP-DOGE	A9 (180°)^{5}	0.171	(0, 0)	A4^{2}	0.172	(0, 0)	A4^{4}	0.123	(0, 0)	E2^{5}	0.081	(0.019, 0.019)
BNB-LTC	A9 (180°)^{2}	0.220	(0, 0)	A9^{3}	0.125	(0, 0)	E2^{2}	0.147	(0.027, 0.027)	A2 (180°)^{3}	0.063	(0, 0.006)
BNB-DOGE	E2^{4}	0.043	(0.003, 0.003)	A9 (180°)^{5}	0.099	(0, 0)	A9^{1}	0.263	(0, 0)	A9^{1}	0.168	(0, 0)
LTC-DOGE	A3 (180°)^{3}	0.144	(0.190, 0)	A9^{1}	0.338	(0, 0)	A4^{3}	0.122	(0, 0)	A8^{4}	0.082	(0.003, 0.063)

For each crypto pair, the fitted bivariate copulae, the Kendall's τ, and the tail dependence (TD) are shown. Symbols representing different bivariate copulae are listed in Table 2. The superscripts on these symbols represent the tree level in the R-vine structures in Fig. 2

bivariate copulae in most of the 15 fitted pairs are Frank (A4) and BB8 (A9), showing weak tail dependency and strong nonlinear dependence in the center of the distribution (see Table 7). Strong upper-tail dependence [the Gumbel copula (A3)] is found in the ETH-BNB and ETH-LTC pairs, while weak symmetric tail-dependence [the Student's T copula (E2)] is observed in the ETH-XRP and BNB-LTC pairs. Once again, strong correlations in the BTC-ETH, ETH-BNB, and XRP-LTC pairs are identified, as discovered in the cases of the log return and log Amihud ratio.

The fitted R-vine structure of the CS estimator is a D-vine copula, as shown in Fig. 2d, where every node has a degree of either one or two, while the maximum node degree in the above three quantities is three. From Table 7, we observe stronger upper-tail dependencies in the majority of the most strongly correlated pairs in Tree 1, except for the XRP-DOGE pair, which gets a Student's T copula (E2) with weak symmetric tail dependence. This differs from the other two liquidity measures, where the non-tail-dependent copulae, Frank (A4) and BB8 (A9), are dominant. Among the 15 fitted copulae, the most frequently selected are Gumbel (A3) and BB7 (A8), which exhibit asymmetric tail dependence. From the lower- and upper-tail coefficient values in Table 7, strong upper-tail dependence is observed in most of the crypto pairs, while their lower-tail dependence coefficients are either zero or relatively small.

In summary, lower-tail dependencies are more common in the case of the log return, while the opposite holds true for the CS liquidity estimator. This observation aligns with the notion that during bearish markets, all crypto prices tend to simultaneously drop, and their liquidity also dries up. For the other two liquidity measures, only weak or no tail-dependencies are mostly observed. Based on these observations, we may conclude that the CS estimator captures the behavior of the crypto market better than the AR estimator during extreme market conditions, suggesting extreme volatility in difficult times (Gao et al. 2019).

BTC and ETH, as the two largest cryptocurrencies, exhibit strong interdependence in both log returns and all liquidity proxies. In addition to ETH, LTC and DOGE demonstrate a strong correlation with BTC in terms of liquidity measures and log returns. ETH displays fairly strong correlations with BNB and LTC, but generally not with XRP and DOGE. XRP exhibits very strong correlations with LTC and only weak correlations with the other coins. Although BNB is less connected to the other cryptos except for ETH, LTC is deeply linked to all the other coins. DOGE also reveals weaker connections to the other cryptos, with the exception of the CS liquidity estimator. From the R-vine-copula tree structure in Tree 1, it is evident that the BTC-ETH, XRP-LTC, and ETH-BNB pairs are consistently directly connected to one another. These three pairs are strongly correlated in all aspects.

Copula between log return and liquidity proxies

In this subsection, we analyze the intra-asset dependence structures between the log returns and liquidity proxies of the six cryptocurrencies. The fitting results using bivariate copulae are presented in Table 8. We find that each crypto's returns are correlated with its own liquidity, with most cryptocurrencies having optimal copulae that are Student's T (E2) with a symmetric tail dependence and small Kendall's τ. This is consistent

Table 8 Fitted bivariate Copula and the corresponding Kendall's τ between the log return and the three liquidity proxies: the log Amihud ratio, the AR estimator, and the CS estimator

Crypto	Log return &	Log Amihud Ratio	AR Estimator	CS Estimator
BTC	Copula	E2	E2	E2
	τ	0.030	0.096	0.034
	(Lower, upper)	(0.173, 0.173)	(0.233, 0.233)	(0.117, 0.117)
ETH	Copula	A5	A5	A5
	τ	0.152	0.227	0.101
	(Lower, upper)	(0, 0.306)	(0, 0.424)	(0, 0.215)
XRP	Copula	A7 (90°)	E2	E2
	τ	− 0.186	0.016	0.021
	(Lower, upper)	(0, 0)	(0.190, 0.190)	(0.101, 0.101)
BNB	Copula	E2	E2	E2
	τ	0.052	0.100	0.034
	(Lower, upper)	(0.185, 0.185)	(0.236, 0.236)	(0.105, 0.105)
LTC	Copula	E2	E2	E2
	τ	0.016	0.099	− 0.008
	(Lower, upper)	(0.186, 0.186)	(0.235, 0.235)	(0.104, 0.104)
DOGE	Copula	E2	E2	E2
	τ	− 0.007	0.004	− 0.010
	(Lower, upper)	(0.154, 0.154)	(0.184, 0.184)	(0.043, 0.043)

with the well-known relationship between return and liquidity proposed by Amihud and Mendelson (1986), where illiquidity leads to an increase in return and vice versa.

This effect is more prominent for the most demanded crypto, ETH, for which the optimal copula between log return and the three liquidity proxies is the Joe copula (A5) function exhibiting more significant Kendall's τ coefficients and stronger upper-tail dependence. This finding indicates that excess return is not correlated with liquidity when the latter is high but is more likely to increase during illiquidity. The least tail dependence is observed for XRP and DOGE, which are less demanded than the other four cryptocurrencies.

Conclusions and outlook

To conclude, our study significantly contributes to the current body of literature on the interrelationships between return and liquidity for individual cryptocurrencies in the marketplace. We conducted a comprehensive quantitative analysis of time-series data for six major cryptocurrencies (BTC, ETH, XRP, BNB, LTC, and DOGE) to eliminate autoregressive and persistent effects through the application of ARIMA and GARCH modeling. By employing the R-vine copula model, we could investigate both the cross-asset dependence in return and liquidity and the intra-asset return-liquidity relationships.

Significant general inter-asset dependencies in return and liquidity were observed among the six examined cryptocurrencies. Among the 15 cryptocurrency pairs, eight pairs displayed an optimal bivariate copula function corresponding to the 180°-rotated Gumbel distribution in terms of return, suggesting a tendency for concurrent price declines rather than rises. The remaining pairs showed weak symmetric tail- dependence in their returns. In terms of the Amihud ratio, an indicator of market-price impact, the optimally fitted correlations are largely central, suggesting that the liquidation of a significant position of one asset does not noticeably influence the liquidation conditions of other assets. Similar conclusions were drawn for the AR estimator of the BAS. However, the CS estimator displayed stronger correlations during market difficulties, a finding more consistent with conventional understanding and indicating a need for further empirical evidence.

The intra-asset tail dependence between return and liquidity was predominantly symmetric and displayed similar values, an observation consistent with findings from traditional markets. This phenomenon can be partially attributed to the demand pressures of corresponding cryptocurrencies.

Our findings provide valuable insights into the underlying dependence structure of cryptocurrency returns and liquidity, which can inform investment strategies and risk-management decisions in this emerging asset class. Our methodology is readily adaptable to encompass all other cryptocurrencies and incorporate dynamic effects. Future research will expand on utilizing these established dependence structures to assist investors and traders in portfolio diversification, asset allocation, risk management, and trading-strategy development. Leveraging our findings, market participants can make informed decisions about their cryptocurrency investments and mitigate their exposure to undue risk. Our study thus represents an important step toward enhancing the overall understanding of the cryptocurrency marketplace and its associated risks and opportunities.

We are confident that the insights gained from our study can facilitate the identification of systemic risks in the cryptocurrency marketplace, thereby enabling the development of effective regulatory policies that ensure market transparency, protect investor interests, and promote global collaboration among regulatory authorities. Consistent with this objective, our future research will delve deeper into the vast, intricate, interconnected, and dynamic cryptocurrency market. For instance, we plan to employ agent-based simulations (Leitch, et al. 2021) to evaluate the effectiveness of various regulatory policies and rules. Our ultimate goal is to create a stable, innovative, and secure financial environment in the digital realm.

Abbreviations

BTC	Bitcoin
ETH	Ethereum
XRP	Ripple
BNB	Binance coin
LTC	Litecoin
DOGE	Dogecoin
ARIMA	Autoregressive integrated moving average
GARCH	Generalized autoregressive conditional heteroskedasticity
OHLC	Open, high, low, and close
BAS	Bid-ask spread
AR	Abdi and Ranaldo
CS	Corwin and Schultz
MLE	Maximum likelihood estimation
JB	Jarque–Bera
LB	Ljung–Box
ADF	Augmented Dickey–Fuller
KPSS	Kwiatkowski–Philips–Schmidt–Shin
R-vine	Regular vine
AIC	Akaike information criterion

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Author contributions
MZ, BZ and ZL contribute equally to this work. YX: Initiated and supervised the project, proof read the manuscript and contributed to the discussion. MZ: Responsible for the preliminary research of the topic and complete the main code of the analysis work. SJ: Editing of the manuscripts and contributed to the discussion of the results. BZ and ZL: Co-supervised the project, led the modeling and discussion, wrote the main part of the manuscript.

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Availability of data and materials
The dataset on which the conclusions of the manuscript rely is a secondary data and it will be made available upon request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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References

Abdi F, Ranaldo A (2017) A simple estimation of bid-ask spreads from daily close, high, and low prices. Rev Financ Stud 30(12):4437–4480. https://doi.org/10.1093/rfs/hhx084
Adhami S, Giudici G, Martinazzi S (2018) Why do businesses go crypto? An empirical analysis of initial coin offerings. J Econ Bus 100:64–75
Ahmed WM (2022) What Determines Bitcoin Liquidity? A Penalized Regression Approach. Appl Econ Lett. https://doi.org/10.1080/13504851.2022.2099793
Almeida J, Gonçalves TC (2023) Portfolio diversification, hedge and safe-haven properties in cryptocurrency investments and financial economics: a systematic literature review. J Risk Financ Manag 16(1):3. https://doi.org/10.3390/jrfm16010003
Al-Yahyaee KH, Mensi W, Ko H-U et al (2020) Why cryptocurrency markets are inefficient: the impact of liquidity and volatility. North Am J Econ Finance 52:101168. https://doi.org/10.1016/j.najef.2020.101168
Amihud Y (2002) Illiquidity and stock returns: cross-section and time-series effects. J Financ Mark 5:31–56
Amihud Y, Mendelson H (1986) Liquidity and stock returns. Financ Anal J 42(3):43–48. https://doi.org/10.2469/faj.v42.n3.43
Anciaux H, Desagre C, Nicaise N, et al (2021) Liquidity co-movements and volatility regimes in cryptocurrencies. In: SSRN scholarly paper. Rochester, NY, https://doi.org/10.2139/ssrn.3769309
Ante L, Sandner P, Fiedler I (2018) Blockchain-based ICOs: Pure hype or the dawn of a new era of startup financing? J Risk Financ Manag 11(4):80
Auer R, Farag M, Lewrick U et al (2022) Banking in the shadow of bitcoin? The institutional adoption of cryptocurrencies. In: BIS working paper no. 1013. pp 1–25
Balli F, de Bruin A, Chowdhury MIH et al (2020) Connectedness of cryptocurrencies and prevailing uncertainties. Appl Econ Lett 27(16):1316–1322
Bedford T, Cooke RM (2002) Vines—a new graphical model for dependent random variables. Ann Stat 30(4):1031–1068. https://doi.org/10.1214/aos/1031689016
Boako G, Tiwari AK, Roubaud D (2019) Vine copula-based dependence and portfolio value-at-risk analysis of the cryptocurrency market. Int Econ 158:77–90. https://doi.org/10.1016/j.inteco.2019.03.002
Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. J Econom 31(3):307–327. https://doi.org/10.1016/0304-4076(86)90063-1
Brauneis A, Mestel R (2018) Price discovery of cryptocurrencies: bitcoin and beyond. Econ Lett 165:58–61. https://doi.org/10.1016/j.econlet.2018.02.001
Brauneis A, Mestel R, Riordan R et al (2018) Bitcoin exchange rates: How integrated are markets? SSRN Sch Pap. https://doi.org/10.2139/ssrn.3249477
Brauneis A, Mestel R, Riordan R et al (2021) How to measure the liquidity of cryptocurrency markets? J Bank Finance 124:106041. https://doi.org/10.1016/j.jbankfin.2020.106041
Brauneis A, Mestel R, Riordan R et al (2022) Bitcoin unchained: determinants of cryptocurrency exchange liquidity. J Empir Finance 69:106–122. https://doi.org/10.1016/j.jempfin.2022.08.004
Brockman P, Chung DY, Pérignon C (2009) Commonality in liquidity: a global perspective. J Financ Quant Anal 44(4):851–882. https://doi.org/10.1017/S0022109009990123

Brunnermeier MK, Pedersen LH (2009) Market liquidity and funding liquidity. Rev Financ Stud 22(6):2201–2238. https://doi.org/10.1093/rfs/hhn098

Canh NP, Wongchoti U, Thanh SD et al (2019) Systematic risk in cryptocurrency market: evidence from DCC-MGARCH model. Finance Res Lett 29:90–100

Cespa G, Foucault T (2014) Illiquidity contagion and liquidity crashes. Rev Financ Stud 27(6):1615–1660. https://doi.org/10.1093/rfs/hhu016

Chan S, Chu J, Zhang Y et al (2022) An extreme value analysis of the tail relationships between returns and volumes for high frequency cryptocurrencies. Res Int Bus Finance 59:101541. https://doi.org/10.1016/j.ribaf.2021.101541

Charfeddine L, Benlagha N, Khediri KB (2022) An intra-cryptocurrency analysis of volatility connectedness and its determinants: evidence from min- ing coins, non-mining coins and tokens. Res Int Bus Finance 62:101699

Chen T-Y, So L-C (2020) Discussion on the effectiveness of the copula-GARCH method to detect risk of a portfolio containing bitcoin. J Math Finance 10(04):499–512. https://doi.org/10.4236/jmf.2020.104030

Chokor A, Alfieri E (2021) Long and short-term impacts of regulation in the cryptocurrency market. Q Rev Econ Finance 81:157–173. https://doi.org/10.1016/j.qref.2021.05.005

Chordia T, Roll R, Subrahmanyam A (2000a) Commonality in liquidity. J Financ Econ 56(1):3–28. https://doi.org/10.1016/S0304-405X(99)00057-4

Chordia T, Roll R, Subrahmanyam A (2000b) Co-Movements in bid-ask spreads and market depth. Financ Anal J 56(5):23–27. https://doi.org/10.2469/faj.v56.n5.2386

Ciaian P, Rajcaniova M et al (2018) Virtual relationships: short-and long-run evidence from BitCoin and altcoin markets. J Int Financ Mark Inst Money 52:173–195

Corbet S, Lucey B, Yarovaya L (2018) Datestamping the Bitcoin and ethereum bubbles. Finance Res Lett 26:81–88

Corwin SA, Schultz P (2012) A simple way to estimate bid-ask spreads from daily high and low prices. J Financ 67(2):719–760. https://doi.org/10.1111/j.1540-6261.2012.01729.x

Cumming DJ, Johan S, Pant A (2019) Regulation of the crypto-economy: managing risks, challenges, and regulatory uncertainty. J Risk Financ Manag 12(3):126. https://doi.org/10.3390/jrfm12030126

Czado C (2019) Analyzing dependent data with vine copulas: a practical guide with R. In: Lecture notes in statistics, vol 222. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-13785-4

da Gama Silva PVJ, Klotzle MC, Pinto ACF et al (2019) Herding behavior and contagion in the cryptocurrency market. J Behav Exp Finance 22:41–50. https://doi.org/10.1016/j.jbef.2019.01.006

Dai H-N, Zheng Z, Zhang Y (2019) Blockchain for internet of things: a survey. IEEE Internet Things J 6(5):8076–8094

De Pace P, Rao J (2023) Comovement and Instability in cryptocurrency markets. Int Rev Econ Finance 83:173–200. https://doi.org/10.1016/j.iref.2022.08.010

Dickey DA, Fuller WA (1981) Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 49(4):1057. https://doi.org/10.2307/1912517

Dimpfl T (2017) Bitcoin market microstructure. SSRN Electron J. https://doi.org/10.2139/ssrn.2949807

Dissmann J, Brechmann EC, Czado C et al (2013) Selecting and estimating regular vine copulae and application to financial returns. Comput Stat Data Anal 59:52–69

Dong B, Jiang L, Liu J et al (2022) Liquidity in the cryptocurrency market and commonalities across anomalies. Int Rev Financ Anal 81:102097. https://doi.org/10.1016/j.irfa.2022.102097

Dyhrberg AH, Foley S, Svec J (2018) How investible is Bitcoin? Analyzing the liquidity and transaction costs of Bitcoin markets. Econ Lett 171:140–143. https://doi.org/10.1016/j.econlet.2018.07.032

Engelhardt MA (2017) Hitching healthcare to the chain: an introduction to blockchain technology in the healthcare sector. Technol Innov Manag Rev 7(10):22–34

Engle RF (1982) Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50(4):987. https://doi.org/10.2307/1912773

Fang F, Ventre C, Basios M et al (2022) Cryptocurrency trading: a compre- hensive survey. Financ Innov 8(1):13. https://doi.org/10.1186/s40854-021-00321-6

Feng L, Shi Y (2017) A simulation study on the distributions of disturbances in the GARCH model. Cogent Econ Finance 5(1). Copyright the Author(s) 2017. Version archived for private and non-commercial use with the permission of the author/s and according to publisher conditions. For further rights please contact the publisher, pp 1–19. https://doi.org/10.1080/23322039.2017.1355503

Fermanian J-D (2017) Recent developments in copula models. Econometrics 5(3):34. https://doi.org/10.3390/econometrics5030034

Fink C, Johann T (2014) Bitcoin markets. SSRN Electron J. https://doi.org/10.2139/ssrn.2408396

Fisch C (2019) Initial coin offerings (ICOs) to finance new ventures. J Bus Ventur 34(1):1–22

Gao Y, Li Y, Wang Y et al (2019) Asymptotic comparison of three spread estimators based on roll's model. Physica A 525:420–432. https://doi.org/10.1016/j.physa.2019.03.044

Garcia-Jorcano L, Benito S (2020) Studying the properties of the bitcoin as a diversifying and hedging asset through a copula analysis: constant and time-varying. Res Int Bus Finance 54:101300. https://doi.org/10.1016/j.ribaf.2020.101300

Geman H, Price H (2021) Bitcoin spot and derivatives markets: searching for completeness. Risk Decis Anal 8(3–4):113–125

Ghabri Y, Guesmi K, Zantour A (2021) Bitcoin and liquidity risk diversification. Finance Res Lett 40:101679. https://doi.org/10.1016/j.frl.2020.101679

Gudgeon L, Perez D, Harz D et al (2020) The decentralized financial crisis. In: pp 1–15

Hartman D, Hlinka J (2018) Nonlinearity in stock networks. Chaos Interdiscip J Nonlinear Sci 28(8):083127

Hartmann P, Straetmans S, Vries CD (2004) Asset market linkages in crisis periods. Rev Econ Stat 86(1):313–326

Hasan M, Naeem MA, Arif M et al (2022) Liquidity connectedness in cryp- tocurrency market. Financ Innov 8(1):3. https://doi.org/10.1186/s40854-021-00308-3

Hasbrouck J, Seppi DJ (2001) Common factors in prices, order flows, and liquidity. J Financ Econ 59(3):383–411. https://doi.org/10.1016/S0304-405X(00)00091-X

Hewa T, Ylianttila M, Liyanage M (2021) Survey on blockchain based smart contracts: applications, opportunities and challenges. J Netw Comput Appl 177:102857. https://doi.org/10.1016/j.jnca.2020.102857
SI Hussain, Ruza N, Masseran N et al (2020) Dependence structure between index stock market and bitcoin using time-varying copula and extreme value theory. In: Proceedings of international conference on advances in materials research (ICAMR-2019). Bangalore, India, p 030002. https://doi.org/10.1063/5.0018079
Ji Q, Bouri E, Lau CKM et al (2019) Dynamic connectedness and integration in cryptocurrency markets. Int Rev Financ Anal 63:257–272
Joe H (1996) Families of m-variate distributions with given margins and $m(m-1)/2$ bivariate dependence parameters. In: Rüschendorf L, Schweizer B, Taylor MD (eds) Distributions with fixed marginals and related topics, vol 28. Institute of Mathematical Statistics, Hayward, pp 120–141. https://doi.org/10.1214/lnms/1215452614
Joe H, Li H, Nikoloulopoulos AK (2010) Tail dependence functions and vine copulas. J Multivar Anal 101(1):252–270
Karolyi GA, Lee K-H, van Dijk MA (2012) Understanding commonality in liquidity around the world. J Financ Econ 105(1):82–112. https://doi.org/10.1016/j.jfineco.2011.12.008
Katsiampa P (2019a) An empirical investigation of volatility dynamics in the cryp- tocurrency market. Res Int Bus Financ 50:322–335
Katsiampa P (2019b) Volatility co-movement between Bitcoin and Ether. Finance Res Lett 30:221–227. https://doi.org/10.1016/j.frl.2018.10.005
Kayal P, Rohilla P (2021) Bitcoin in the economics and finance literature: a survey. SN Bus Econ 1(7):88
Kim J-M, Kim S-T, Kim S (2020) On the relationship of cryptocurrency price with US stock and gold price using copula models. Mathematics 8(11):1859. https://doi.org/10.3390/math8111859
Koenraadt J, Leung E (2022) Investor reactions to crypto token regulation. Eur Account Rev. https://doi.org/10.1080/09638180.2022.2090399
Koutmos D (2018) Return and volatility spillovers among cryptocurrencies. Econ Lett 173:122–127
Kwiatkowski D, Phillips PC, Schmidt P et al (1992) Testing the null hypothesis of stationarity against the alternative of a unit root. J Econom 54(1–3):159–178. https://doi.org/10.1016/0304-4076(92)90104-Y
Leirvik T (2022) Cryptocurrency returns and the volatility of liquidity. Finance Res Lett 44:102031. https://doi.org/10.1016/j.frl.2021.102031
Leitch M, Mainelli M et al (2021) Eternal coins? Control and regulation of alternative digital currencies
Lengyel-Almos KE, Demmler M (2021) Is the Bitcoin market efficient? A literature review. Anál Econ 36(93):167–187
Ljung GM, Box GEP (1978) On a measure of lack offitin time series models. Biometrika 65(2):297–303. https://doi.org/10.1093/biomet/65.2.297
Loi H (2017) The liquidity of Bitcoin. Int J Econ Financ 10(1):13. https://doi.org/10.5539/ijef.v10n1p13
Ma R, Marshall BR, Nguyen NH et al (2022) Does Bitcoin liquidity resemble the liquidity of other financial assets? Aust J Manag 47(4):729–748. https://doi.org/10.1177/03128962211069615
Makarov I, Schoar A (2019) Price discovery in cryptocurrency markets. AEA Pap Proc 109:97–99. https://doi.org/10.1257/pandp.20191020
Manahov V (2021) Cryptocurrency liquidity during extreme price movements: is there a problem with virtual money? Quant Finance 21(2):341–360
Manimuthu A, Rejikumar G, Marwaha D et al (2019) A literature review on Bitcoin: transformation of crypto currency into a global phenomenon. IEEE Eng Manage Rev 47(1):28–35
Mantalos P (2011) Three different measures of sample skewness and kurtosis and their effects on the jarque bera test for normality. Int J Comput Econ Econom 2(1):47. https://doi.org/10.1504/IJCEE.2011.040576
Markowitz H (1952) Portfolio selection. J Finance 7(1):77–91
Marshall BR, Nguyen NH, Visaltanachoti N (2019) Bitcoin liquidity. In: SSRN scholarly paper. Rochester, NY, https://doi.org/10.2139/ssrn.3194869
McNeil AJ, Nešlehová J (2009) Multivariate archimedean copulas, d-monotone functions and L1-norm symmetric distributions. Ann Stat 37(5B):3059–3097. https://doi.org/10.1214/07-AOS556
Mokni K, Mansouri F (2017) Conditional dependence between international stock markets: a long memory GARCH-copula model approach. J Multinatl Financ Manag 42:116–131
Moreno D, Antoli M, Quintana D (2022) Benefits of investing in cryptocurrencies when liquidity is a factor. Res Int Bus Finance 63:101751. https://doi.org/10.1016/j.ribaf.2022.101751
Naeem M, Saleem K, Ahmed S et al (2020) Extreme return-volume relationship in cryptocurrencies: tail dependence analysis. Cogent Econ Finance 8(1):1834175. https://doi.org/10.1080/23322039.2020.1834175
Naeem M, Bouri E, Boako G et al (2020) Tail dependence in the return- volume of leading cryptocurrencies. Finance Res Lett 36:101326. https://doi.org/10.1016/j.frl.2019.101326
Nakamoto S (2008) Bitcoin: a peer-to-peer electronic cash system. In: Decentralized business review, p 21260
Owais M, Gulzar S et al (2020) Return spillover across Bitcoin markets and foreign exchange pairs dominated in major trading currencies. Bus Econ Rev 12(3):123–160
Pradhan AK, Mittal I, Tiwari AK (2021) Optimizing the market-risk of major cryptocurrencies using CVaR measure and copula simulation. Macroecon Finance Emerg Mark Econ 14(3):291–307. https://doi.org/10.1080/17520843.2021.1909828
Qarni MO, Gulzar S (2021) Portfolio diversification benefits of alternative currency investment in Bitcoin and foreign exchange markets. Financ Innov 7(1):1–37
Queiroz MM, Telles R, Bonilla SH (2020) Blockchain and supply chain management integration: a systematic review of the literature. Supply Chain Manag Int J 25(2):241–254
Righi MB, Ceretta PS (2013) Estimating non-linear serial and cross-interdependence between financial assets. J Bank Finance 37(3):837–846
Sadegh M, Ragno E, AghaKouchak A (2017) Multivariate copula analysis toolbox (MvCAT): describing dependence and underlying uncertainty using a Bayesian framework. Water Resour Res 53(6):5166–5183. https://doi.org/10.1002/2016WR020242

Saleemi J (2021) COVID-19 uncertainty and Bitcoin market, linking the liquidity cost to the cryptocurrency yields. Finance Mark Valuat 7(1):1–11. https://doi.org/10.46503/BJWT6248
Scharnowski S (2021) Understanding Bitcoin Liquidity. Finance Res Lett 38:101477. https://doi.org/10.1016/j.frl.2020.101477
Schweizer B, Wolff EF (1981) On nonparametric measures of dependence for random variables. Ann Stat 9(4):879–885. https://doi.org/10.1214/aos/1176345528
Sebastião H, Godinho P (2021) Forecasting and trading cryptocurrencies with machine learning under changing market conditions. Financ Innov 7(1):3. https://doi.org/10.1186/s40854-020-00217-x
Shi S (2017) The impact of futures trading on intraday spot volatility and liquidity: evidence from Bitcoin market. SSRN Electron J. https://doi.org/10.2139/ssrn.3094647
Shumway RH, Stoffer DS (2017) ARIMA models. In: Time series analysis and its applications. Springer Texts in Statistics. Springer International Publishing, Cham, pp 75–163. https://doi.org/10.1007/978-3-319-52452-8_3
Sklar M (1959) Fonctions de repartition an dimensions et leurs marges. Publ Inst Statist Univ Paris 8:229–231
So MKP, Chu AMY, Lo CCY et al (2022) Volatility and dynamic dependence modeling: Review, applications, and financial risk management. WIREs Comput Stat 14(5):e1567. https://doi.org/10.1002/wics.1567
Sun J, Yan J, Zhang KZ (2016) Blockchain-based sharing services: what blockchain technology can contribute to smart cities. Financ Innov 2(1):1–9
Syuhada K, Hakim A (2020) Modeling risk dependence and portfolio VaR forecast through vine copula for cryptocurrencies. PLOS ONE 15(12):1–34. https://doi.org/10.1371/journal.pone.0242102
Tang T, Wang Y (2022) Liquidity shocks, price volatilities, and riskmanaged strategy: evidence from Bitcoin and beyond. J Multinatl Financ Manag 64:100729. https://doi.org/10.1016/j.mulfin.2022.100729
Tenkam HM, Mba JC, Mwambi SM (2022) Optimization and diversification of cryptocurrency portfolios: a composite copula-based approach. Appl Sci 12(13):6408. https://doi.org/10.3390/app12136408
Theiri S, Nekhili R, Sultan J (2022) Cryptocurrency liquidity during the russia-ukraine war: the case of bitcoin and ethereum. J Risk Finance. https://doi.org/10.1108/JRF-05-2022-0103
Tiwari AK, Adewuyi AO, Albulescu CT et al (2020) Empirical evidence of extreme dependence and contagion risk between main cryptocurrencies. North Am J Econ Finance 51:101083. https://doi.org/10.1016/j.najef.2019.101083
Tootoonchi F, Haerter JO, Räty O et al (2020) Copulas for hydroclimatic applications: a practical note on common misconceptions and pitfalls. Hydrol Earth Syst Sci Discuss 2020:1–31. https://doi.org/10.5194/hess-2020-306
Tripathi A, Dixit A, Vipul (2022) Liquidity commonality in the cryptocurrency market. Appl Econ 54(15):1727–1741. https://doi.org/10.1080/00036846.2021.1982128
van den End JW, Tabbae M (2012) When liquidity risk becomes a systemic issue: empirical evidence of bank behaviour. J Financ Stab 8(2):107–120. https://doi.org/10.1016/j.jfs.2011.05.003
Vidyamurthy G (2004) Pairs trading: quantitative methods and analysis, vol 217. Wiley, Hoboken
Wei WC (2018) Liquidity and market efficiency in cryptocurrencies. Econ Lett 168:21–24. https://doi.org/10.1016/j.econlet.2018.04.003
Xu M, Chen X, Kou G (2019) A systematic review of blockchain. Financ Innov 5(1):27. https://doi.org/10.1186/s40854-019-0147-z
Xu Q, Zhang Y, Zhang Z (2021) Tail-risk spillovers in cryptocurrency markets. Financ Res Lett 38:101453
Yarovaya L, Zięba D (2022) Intraday volume-return nexus in cryptocurrency markets: novel evidence from cryptocurrency classification. Res Int Bus Finance 60:101592. https://doi.org/10.1016/j.ribaf.2021.101592
Yi S, Xu Z, Wang G-J (2018) Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? Int Rev Financ Anal 60:98–114
Zetzsche DA, Buckley RP, Arner DW et al (2018) The ICO gold rush: it's a scam, it's a bubble, it's a super challenge for regulators. In: SSRN scholarly paper. Rochester, NY, https://doi.org/10.2139/ssrn.3072298
Zhang Z (2021) On studying extreme values and systematic risks with nonlinear time series models and tail dependence measures. Stat Theory Relat Fields 5(1):1–25. https://doi.org/10.1080/24754269.2020.1856590
Zhang Y, Chan S, Chu J et al (2020) On the market efficiency and liquidity of high-frequency cryptocurrencies in a bull and bear market. J Risk Financ Manag 13(1):8. https://doi.org/10.3390/jrfm13010008
Zivot E (2009) Practical issues in the analysis of univariate GARCH models. In: Mikosch T, Kreiß J-P, Davis RA et al (eds) Handbook of financial time series. Springer, Berlin, pp 113– 155. https://doi.org/10.1007/978-3-540-71297-8_5
Zulfiqar N, Gulzar S (2021) Implied volatility estimation of bitcoin options and the stylized facts of option pricing. Financ. Innov. 7:1–30

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