Financial Innovation

RESEARCH

Open Access

Cryptocurrencies under climate shocks: a dynamic network analysis of extreme risk spillovers

Kun Guo[1,2], Yuxin Kang[2,3], Qiang Ji[4*] and Dayong Zhang[5]

*Correspondence: jqwxnjq@163.com

[1] School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China
[2] Research Center On Fictitious Economy & Data Science, Chinese Academy of Science, Beijing 100190, China
[3] Sino-Danish College, University of Chinese Academy of Sciences, Beijing 100190, China
[4] Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China
[5] Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu 611130, China

Abstract

Systematic risks in cryptocurrency markets have recently increased and have been gaining a rising number of connections with economics and financial markets; however, in this area, climate shocks could be a new kind of impact factor. In this paper, a spillover network based on a time-varying parametric-vector autoregressive (TVP-VAR) model is constructed to measure overall cryptocurrency market extreme risks. Based on this, a second spillover network is proposed to assess the intensity of risk spillovers between extreme risks of cryptocurrency markets and uncertainties in climate conditions, economic policy, and global financial markets. The results show that extreme risks in cryptocurrency markets are highly sensitive to climate shocks, whereas uncertainties in the global financial market are the main transmitters. Dynamically, each spillover network is highly sensitive to emergent global extreme events, with a surge in overall risk exposure and risk spillovers between submarkets. Full consideration of overall market connectivity, including climate shocks, will provide a solid foundation for risk management in cryptocurrency markets.

Keywords: Cryptocurrencies, Extreme risk, Climate shocks, Uncertainty, Spillover effects

Introduction

In recent years, the cryptocurrency market has witnessed a significant surge in trading volume and market capitalization, which can be attributed to the proliferation of numerous cryptocurrencies following the 2017 bull market. With the market capitalization of the cryptocurrency industry exceeding $1 trillion at the start of 2021, the cryptocurrency market has attracted a wide range of institutional and retail investors. However, in the expansion path of the cryptocurrency market, investors have experienced a series of bubbles and crashes (Chowdhury et al. 2022). There is a possibility of a complete collapse in cryptocurrency prices (Fry 2018). For example, Bitcoin's value plummeted by 99% in a single day in June 2011, and the global cryptocurrency market experienced the evaporation of one trillion dollars in market value within one week in May 2021. The complex dynamics between the main elements in the cryptocurrency market (Ji et al. 2019a; Antonakakis et al. 2020) have drawn public and academic attention to the systemic risk of various cryptocurrencies and the overall cryptocurrency market (Canh et al. 2019; Akhtaruzzaman et al. 2022). Bitcoin, the largest cryptocurrency based on market capitalization, is often viewed as an important safe haven asset and portfolio diversifier (Bouri et al. 2017). However, as cryptocurrencies become increasingly intertwined with other markets, the volatility and uncertainty in these markets or economic systems can be rapidly contagious within the cryptocurrency market. Consequently, Bitcoin's effectiveness as a safe haven during risk contagion has come under scrutiny (Klein et al. 2018; Conlon and McGee 2020).

As the economic and social impacts of climate change expand, climate shocks will also have a series of profound impacts on financial markets, including cryptocurrency markets (Martinez-Diaz and Keenan 2020; Fernando et al. 2021). Hasselmann (1997) noted the significant uncertainty present in both climate and economic systems, requiring appropriate climate policies. These policies should address a range of possible scenarios, developed with full consideration of such uncertainty. In global climate mitigation and adaptive actions, socioeconomic and climate scenarios are often examined together to analyze vulnerability to climate change (Berkhout et al. 2014). However, uncertainties in socioeconomic systems and their interactions with the climate system are more complex than those in the climate system itself (Schelling 2009; Giupponi et al. 2013). Cryptocurrency markets are interconnected with financial and economic systems, and shocks to financial markets from climate risk can spill over into cryptocurrency markets. Especially when considering the association between cryptocurrency properties and climate risk, climate risk can impact cryptocurrency markets through these mechanisms. Specifically, because of the production nature of cryptocurrencies, proof-of-work (PoW) algorithms for cryptocurrencies, such as Bitcoin, are designed to incentivize electricity consumption. Not all mining practices use low-carbon electricity, and greenhouse gas emissions from the attendant massive increase in fossil fuel power generation contribute to climate change (Stoll et al. 2019; Schinckus et al. 2020; Milunovich 2022). The embedded carbon footprint of cryptocurrency transactions in relation to environmental sustainability is of great concern (Corbet et al. 2021). Globally, increased cryptocurrency-related activities have been shown to have negative externalities and are environmentally unsustainable (Vranken 2017; Mora et al. 2018). For example, carbon mitigation actions in countries such as China and the United States may be affected (Jiang et al. 2021a). Research on the interconnections between cryptocurrency markets and other financial markets as well as economic policies has gained academic attention. Previous studies have focused on the interconnections and risk spillovers within cryptocurrency markets or between cryptocurrency markets and traditional financial markets. However, less attention has been paid to the importance of climate shocks. When the risk connectedness between cryptocurrencies and other markets has been examined in previous studies, Bitcoin volatility has been used mostly as a proxy for cryptocurrency market volatility, with less consideration of the overall extreme risk of the cryptocurrency market. However, the embedded carbon footprint of cryptocurrency trading and the close connection of cryptocurrency markets to other markets also enable climate shocks to be transmitted to cryptocurrency markets through both direct and indirect channels. Therefore, this study first measures the extreme risk of different cryptocurrencies using the value at risk (VaR) method. The time-varying parameter-vector autoregression (TVP-VAR) model is then employed to construct extreme spillover networks for cryptocurrency markets based on upside and downside risks, respectively. The overall connectedness risk of cryptocurrency markets can be measured from the network. Then, the second TVP-VAR-DY connectedness network is built, here considering climate risk as a new uncertainty, along with uncertainties in policy and in the capital, financial, oil, and gold markets.

The rest of this paper is structured as follows: Sect. "Literature Review" presents a literature review; Sect. "Methodology and Data" introduces the methodology and data; Sects. "Empirical Analysis" and "Robustness Tests" provide the empirical analysis and robustness tests, respectively; and Sect. "Conclusion" concludes the paper.

Literature review

Research on cryptocurrency markets and traditional uncertainties

With the rapid integration of various cryptocurrencies into traditional financial markets, considerable effort has been expended on the factors of cryptocurrency volatility, including endogenous factors, exogenous influences such as exchange rate markets, stock markets, bond markets, gold markets, and economic policy uncertainty.

Endogenous factors, which involve the interaction of cryptocurrencies (Ji et al. 2019b) and exchanges (Ji et al. 2018) could not be ignored. Soylu et al. (2020) studied the long-memory property of three major cryptocurrencies—Bitcoin, Ethereum, and Ripple—and found that their squared returns all had long memory and could be fitted using a family of GARCH models. Regarding the volatility dynamics of the cryptocurrency market, scholars have applied different estimation methods to study spillover effects among digital currencies. Koutmos (2018) investigated the interdependence of 18 major cryptocurrencies, such as Bitcoin, based on the volatility spillover framework of vector autoregression (VAR) with variance decomposition proposed by Diebold and Yilmaz (2009). The results indicated that Bitcoin was the main risk dominating the connectedness network and that the strength of the spillover effect of cryptocurrency returns and volatility, which gradually increased over time, increased the risk of contagion.

Although there are essential differences between cryptocurrencies and sovereign currencies of leading countries, especially treasury bonds which are often perceived as safe havens, they are still inextricably linked (Ji et al. 2018). Aharon et al. (2021) showed the dynamics between the historical volatility of exchange rates of the main fiat currencies in Canada, Switzerland, the European Union, Japan, the UK, and Bitcoin. Hsu et al. (2021) used a diagonal BEKK model to investigate the risk spillovers of three major cryptocurrencies to traditional currencies and found significant volatility spillover effects between cryptocurrencies and traditional currencies, especially during the COVID-19 pandemic. Other researchers arrived at similar conclusions (Peng et al. 2018; Andrada-Félix et al. 2020). In response to the surge in cryptocurrencies, numerous central banks have introduced central bank digital currencies (CBDCs) to tackle the challenges posed by the potential impacts of cryptocurrencies (Wang et al. 2022). Wang et al. (2023) established the TVP-VAR-DY and TVP-VAR-BK models to examine the risk spillovers between the Central Bank Digital Currency Attention Index (CBDCAI) and the cryptocurrency market. They found that CBDCAI has a significant risk spillover effect on the cryptocurrency market, thereby impacting its prices. The relationship between cryptocurrencies and the financial market has been analyzed in detail over the past decade. Regarding the stock market, Gil-Alana et al. (2020) provided evidence of the significant role of cryptocurrencies in investor portfolios, which have served as a diversification option. Cryptocurrencies and stock markets have remained correlated throughout the COVID-19 pandemic (Caferra and Vidal-Tomás 2021) in various countries (Jiang et al. 2021b). In terms of bonds, comparing three bond markets (BBGT, SPGB, and SKUK), Karim et al. (2022) measured the hedge and safe haven characteristics of three cryptocurrency indices (UCRPR, UCRPO, and ICEA), revealing that SPGB outperformed other bonds and provided effective diversification for cryptocurrency indices. Even in developing countries, cryptocurrencies have hedging potential (Hartono and Robiyanto 2021).

Moreover, considering investment substitutions, both cryptocurrencies (e.g., Bitcoin) and gold have shown diversification (Brière et al. 2015), as well as hedging capabilities (Dyhrberg 2016), with the return and volatility connectedness among the cryptocurrency and gold markets analyzed in the literature. Ozturk (2020) showed that there was a correlation between Bitcoin and the gold market, and that medium and high frequencies are the main influences on the correlation of returns and volatility, respectively. Intriguingly, energy markets (Ji et al. 2019a, b), oil markets (Okorie and Lin 2020; Ozturk 2020) and carbon prices (Pham et al. 2022), among other factors, have been found to play a role in cryptocurrency volatility.

Macroeconomic and policy uncertainties have been well established in the literature as greatly impacting the volatility of traditional financial markets as well as cryptocurrency markets. Ghosh et al. (2022) employed the DCC-GJR-GARCH and quantile cross-spectral models to investigate the impact of uncertainty in economic and trade policies on the stock markets of China and the United States. This study revealed that the economic and trade policy uncertainty between the two countries resulted in a pronounced clustering effect of high volatility in their respective stock markets. Moreover, changes in China's cryptocurrency policy have been negatively associated with Bitcoin and Litecoin volatility (Yen and Cheng 2021). Kwon (2021) found that a 1% VaR for Bitcoin had a positive relationship with the US economic policy uncertainty index. In the cryptocurrency market, informed and institutional investors demonstrate greater sensitivity to changes in both price and policy uncertainty, as opposed to solely reacting to price fluctuations (Lucey et al. 2022). Other macroeconomic uncertainties, including global economic policy uncertainty (Fang et al. 2020), cryptocurrency policy uncertainty (Elsayed et al. 2022), systemic risks in the global financial market (Li and Huang 2020), and global geopolitical risks (Aysan et al. 2019; Bouri et al. 2021a, b; Kyriazis 2020; Su et al. 2020) also influence the volatility of cryptocurrencies.

Behavioral finance factors such as internet attention (Zhang et al. 2021) and investor attractiveness (Al Guindy 2021; Bouri et al. 2021a, b; das Neves, 2020), have also been included when analyzing the factors influencing cryptocurrency markets. Zhang et al. (2021) employed a time-varying causality method to examine the relationship between trading volume, returns, and internet attention in the global Bitcoin market. They found that Bitcoin internet attention had a strong Granger causality relationship with trading volume and that Bitcoin returns had a strong impact on internet attention but not vice versa, which was shown to increase with extreme price fluctuations.

Research on cryptocurrency markets and climate shocks

The interaction of the climate system with the financial system has introduced new uncertainties into the entire system (Giupponi et al. 2013). Climate shocks can weigh on capital markets (e.g., stocks, bonds, commodities, and crude oil). Global warming has placed pressure on policymakers to develop green economies, with financial resources and capital being encouraged to increasingly flow away from fossil fuels and towards non-fossil energy sources (OECD 2017). This accelerated energy transition and economic electrification pose price risks to energy companies (Fernandes et al. 2021). Similarly, stock market returns depend on climate change-related risks and are subject to higher-intensity shock spillovers in depressed and booming market states (Khalfaoui et al. 2022). However, as an alternative investment, cryptocurrency market prices are correlated with prices in these markets and may be accompanied by risk spillovers from climate shocks to cryptocurrency markets.

Furthermore, the increasingly active cryptocurrency market will impact global electricity consumption, the environment, and climate (Stoll et al. 2019; Schinckus et al. 2020). Specifically, because PoW is the consensus algorithm that underpins cryptocurrencies such as Bitcoin, cryptocurrency transactions consume large amounts of electricity (Milunovich 2022). Cryptocurrencies such as Bitcoin operate on decentralized computer networks, employing algorithms that involve solving hash function puzzles to verify transactions and provide rewards to successful validators known as cryptocurrency miners. The surge in cryptocurrency prices has resulted in substantial mining rewards, attracting a growing amount of computational power to participate in mining processes. However, this trend also results in significant energy consumption and a notable increase in the carbon footprint (Wendl et al. 2023). Empirical findings have demonstrated the impact of cryptocurrency energy use on the pricing of large electricity markets (Corbet et al. 2021). The significant growth in the carbon footprint caused by such mechanisms within blockchain networks, coupled with the industry's lack of a proactive attitude towards technological adjustments for energy reduction, poses a severe threat to achieving the net-zero carbon emissions goal by 2050, as proposed at COP26[1] (Truby et al. 2022). To mitigate the environmental impact of the energy-intensive mining mechanism associated with cryptocurrencies, Ethereum has adopted a lower-energy-demanding consensus mechanism called the "proof of stake" (PoS) as a replacement for the traditional PoW. However, extending this alternative solution to other cryptocurrencies presents several challenges (De Vries 2023). Energy consumption and the associated carbon footprint growth inherent in the development of the cryptocurrency market have raised concerns about the environmental risks associated with this market and its underlying technologies (Ren and Lucey 2022). Thus, climate shocks may generate risk spillovers to the cryptocurrency market through mechanisms such as changes in investor attention, information transmission between markets, and regulatory policies. Although many scholars have studied the relationship between cryptocurrency markets and financial markets, climate risk, and economic systems, few have comprehensively

[1] UN Climate Change Conference UK 2021 https://ukcop26.org/, accessed 20 June 20, 2023.

examined risk transmission between economic and financial systems, including cryptocurrency markets and climate risk, in an integrated manner.

Hence, this study has constructed two spillover networks. The first network examines the extreme risks of cryptocurrencies, whereas the second encompasses a spectrum of uncertainties in climate conditions, economic policy, and the global financial market. The objective is to analyze the transmission of risks between these diverse uncertainties and the extreme risks associated with cryptocurrencies.

Previous research has predominantly examined the cryptocurrency market through the lens of returns, volatility, trading volume, realized volatility, and implied volatility (Aalborg et al. 2019; Akyildirim et al. 2020; Bonaparte 2023). The prices of cryptocurrencies such as Bitcoin have experienced significant volatility in recent years, highlighting the need for investors to be vigilant about extreme risk (Bouri et al. 2019; Naeem et al. 2022). Accordingly, our study explores the interrelationships among cryptocurrencies from the perspective of extreme risk. Moreover, when investigating the dynamic connectedness between extreme risk and other sources of uncertainty within the cryptocurrency market, our analysis extends beyond solely employing Bitcoin as a representative of the cryptocurrency market because we encompass five other prominent cryptocurrencies within our analytical framework.

In addition, we deviate from conventional examinations of the factors influencing the cryptocurrency market, which typically include financial markets, energy markets, and policy uncertainty. Instead, we introduce an innovative factor, namely, climate risk. Climate risk affects the cost of currency issuance through its influence on the fuel prices that power cryptocurrencies, holding the potential to transmit risks to the cryptocurrency market via climate shocks that can reverberate across financial markets. Notably, in terms of characterizing climate risk, previous studies have commonly employed physical risk as a measure (Hong et al. 2019; Addoum et al. 2020). Conversely, our study has adopted an approach that utilized Google Trends data encompassing the terms "climate risks," "climate change," and "global warming." By selecting these three keywords from Google Trends, we gauged climate risk from the perspective of societal concerns, thereby introducing a new dimension to our analysis.

Methodology and data

Methodology

TVP-VAR-DY approach

In this study, we utilized the vector autoregressive method with time-varying parameters (TVP-VAR) combined with the generalized variance decomposition-based spillover index method to build overall risk spillover networks (Diebold and Yilmaz 2009; Antonakakis et al. 2020). The TVP-VAR method overcomes the limitations of the traditional rolling-window VAR method in terms of sample loss, window width selection, and outlier effects. It also incorporates time-varying intercept terms and stochastic volatility (SV), making volatility spillover estimates comparable across periods and insensitive to outliers (Antonakakis et al. 2020). Based on the volatility series of each market return, the TVP-VAR model is first constructed and then transformed into a vector moving average (VMA) model. This is followed by the variance decomposition correlation matrix obtained by H-step prediction variance decomposition, on which the dynamic correlation index of market risk spillover in each period is calculated.

We define the daily return volatility of market i as $y_{i,t}$, here considering the total volatility vector for m markets $y_t = (y_{1,t}, ..., y_{m,t})\prime$; Hence, the TVP-VAR(p) model with y_t series satisfied is constructed as follows:

$$y_t = A_t z_{t-1} + \epsilon_t \epsilon_t | \Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t \xi_t | \Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

with

$$z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \cdots \\ y_{t-p} \end{pmatrix} A_t' = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \cdots \\ A_{pt} \end{pmatrix}$$

where Ω_{t-1} represents all known information up to period t-1. To estimate the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD), it is essential to compute them in a generalized linkage estimation (Koop et al. 1996; Pesaran and Shin 1998; Diebold and Yılmaz 2014). Following Koop and Korobils (2013), we integrate a Kalman filter with a forgetting factor into the TVP-VAR model, allowing for the differential weighting of historical estimates and recent observations. This adaptive mechanism enhances the responsiveness of the model to changes resulting from high-dimensional data. Based on the seminal works, benchmark values for the forgetting factor, specifically κ_1=0.99 and κ_2=0.96, are chosen to guide the analysis. Based on the time-varying parameters and matrix results of the Kalman filter estimation model with forgetting factors and the Wold representation theorem, the TVP-VAR model is transformed into the corresponding VMA model:

$$y_t = \sum_{j=0}^{\infty} B_{jt} \epsilon_{t-j} \tag{3}$$

where B_{jt} is an $m \times m$ dimensional matrix. The generalized error variance decomposition of H-step that forecasts GFEVD($\widetilde{\phi}_{ij,t}(H)$) is performed based on the VMA model to obtain the $m \times m$ dimensional generalized variance decomposition matrix. Each element of the matrix reflects the proportion of the H-step forecast variance of the total volatility of market i which is contributed by the market j disturbance. The pairwise directional connectedness $\widetilde{\phi}_{ij,t}(H)$ from j to i is calculated by the following:

$$\widetilde{\phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j-1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{4}$$

with $\sum_{j=1}^{m} \widetilde{\phi}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m} \widetilde{\phi}_{ij,t}(H) = m$

where $\Psi_{ij,t}(H)$ is the GIRF, representing the responses of all other markets j to the shock in market i. The dynamic correlation index (DY) of the risk spillover can be calculated based on the results of the variance decomposition of the total volatility of each market.

The total connectedness index (TCI) illustrates the overall risk spillover within the network of risk spillovers constructed by all markets:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \widetilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \widetilde{\phi}_{ij,t}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \widetilde{\phi}_{ij,t}(H)}{m} \times 100 \tag{5}$$

The directional spillover index reflects the spillover relationship between a given market and all other markets, including the spillover, spill-in, and net spillover indices. Among them, the total directional connectedness to others (TO) indicates the total spillover effect of market i in period t to all other markets:

$$C_{i\to\bullet,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \widetilde{\phi}_{ji,t}(H)}{\sum_{j=1}^{m} \widetilde{\phi}_{ji,t}(H)} \times 100 = \sum\nolimits_{j=1,i\neq j}^{m} \widetilde{\phi}_{ji,t}(H) \times 100 \tag{6}$$

The total directional connectedness from others (FROM) denotes the total spillover to market i in period t from all other markets:

$$C_{i\leftarrow\bullet,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \widetilde{\phi}_{ij,t}(H)}{\sum_{j=1}^{m} \widetilde{\phi}_{ij,t}(H)} \times 100 = \sum\nolimits_{j=1,i\neq j}^{m} \widetilde{\phi}_{ij,t}(H) \times 100 \tag{7}$$

The total directional connectedness TO minus the total directional connectedness from others (FROM) yields the net total directional connectedness (NET), which represents the influence of market i on all other markets:

$$C_{i,t} = C_{i\to\bullet,t}(H) - C_{i\leftarrow\bullet,t}(H) \tag{8}$$

To examine bilateral directional relationships, the net pairwise directional connectedness (NPDC) between two markets indicates the net spillover effect of market i on market j:

$$NPDC_{ij}(H) = (\widetilde{\phi}_{ji,t}(H) - \widetilde{\phi}_{ij,t}(H)) \times 100 \tag{9}$$

We built upside and downside risk spillover networks for the overall cryptocurrency market and constructed a cryptocurrency market time-varying TCI to estimate extreme risks for the cryptocurrency markets (CRYPTOVU and CRYPTOVD for the upside and downside risks, respectively). For the second TVP-VAR-DY connectedness network, various types of uncertainties, including climate, financial, policy, international capital market, oil, gold, and bond risks, are considered to study the spillover effects between each type of uncertainty and the overall extreme risk of the cryptocurrency market. EViews software and R language were utilized for data analysis, and R language was used for model construction.

Data and indicators

Measurement of extreme risk in the cryptocurrency market

To measure extreme risk in the cryptocurrency market, the price data of representative cryptocurrencies are used to estimate the volatility VAR of various currencies. JPMorgan and Reuters created the VAR risk metric in 1994, after which VAR began to be applied to market extreme risk calculations in many other industries, such as banking. Based on this, we have established the first layer of the dynamic risk spillover network and constructed the total cryptocurrency market risk spillover indexes CRYPTOVU and CRYPTOVD as proxy variables for extreme upside and downside risks in the cryptocurrency market.

VAR is used to measure the extreme risk of various cryptocurrency assets and to calculate volatility connectedness to measure the volatility of various cryptocurrency markets. Cryptocurrency returns $r_{i,t}$ are calculated as log changes of the closing price for each currency, which can be denoted as follows:

$$r_{i,t} = lnP_{i,t} - lnP_{i,t-1} \tag{10}$$

where $r_{i,t}$ represents the returns of cryptocurrency i in period t and $P_{i,t}$ denotes the closing price of cryptocurrency i in period t.

The upside risk and downside risk are calculated as follows:

$$VaR_{i,t}^{U,\alpha} = \mu_{it} + t_{i,t}^{-1}(1-\alpha)\sigma_{it} \tag{11}$$

$$VaR_{i,t}^{D,\alpha} = \mu_{it} - t_{i,t}^{-1}(1-\alpha)\sigma_{it} \tag{12}$$

where $VaR_{i,t}^{U,\alpha}$ and $VaR_{i,t}^{D,\alpha}$ represent the upside and downside risk of asset i in period t, respectively;μ_{it} and σ_{it} represent the conditional mean and normalized residuals of the return series, respectively; and $t_{i,t}^{-1}(1-\alpha)$ represents the quantile of the skewed t-distribution at α level.

The Autoregressive Moving Average (ARMA) model, ARMA(m,n), is employed to describe the mean equation of the return series as follows:

$$r_t = \mu + \sum\nolimits_{i=1}^{m} \varnothing_i r_{t-i} + \sum\nolimits_{j=1}^{n} \theta_j \varepsilon_{t-j} \tag{13}$$

$$\varepsilon_t = z_t \sqrt{\sigma_t} z_t \sim N(01) \tag{14}$$

where $\mathrm{r_t}$ denotes the return on the asset in period t and m and n are the lagged orders of the autoregressive and moving average terms of the ARMA(m,n) model, respectively.

Referring to Bollerslev (1986), we use the generalized autoregressive conditional heteroskedasticity model GARCH(p,q) to estimate the conditional variance of the return series:

$$\sigma_t^2 = \alpha_0 + \sum\nolimits_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum\nolimits_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{15}$$

where σ_t^2 denotes conditional variance , ε_t^2 is a disturbance term, and q and p are the lag order of ε_t^2 and autoregressive order ofσ_t^2, respectively.

Measurement of uncertainties

Referring to Ji et al. (2019a, b), we classify the uncertainties that may influence cryptocurrency markets into four categories: climate, policy, global financial, and investment substitution uncertainties. For climate risk (CLM), "climate change," "climate risk," and "global warming" are selected as keywords to construct Google Search Volume Index (GSVI). Second, the logarithm of the GSVI at each time point is subtracted from the logarithm of the median GSVI of the previous 60 days to calculate the abnormal GSVI (AGSVI) to represent climate uncertainty. The median of the selected longer time window captures the normal level of GSVI (DA et al. 2011), and the AGSVI constructed based on this can provide a more direct indication of additional concerns from the internet (Zhang et al. 2021). For policy uncertainty, the US economic policy uncertainty index—EPU—is chosen as a proxy. For global financial uncertainty, we consider international capital market risk and financial risk. The S&P 500 panic index (VIX) measures the international capital market risk. Additionally, the global financial stress index (OFR FSI is chosen as a measure of financial risk. For investment substitution uncertainty, we consider the following four market aspects: oil risk (OVX), gold risk (GVZ), exchange rate risk (DXY), and bond risk (BT). The CBOE Crude Oil Volatility Index and CBOE Gold ETF Volatility Index are used as proxies for oil risk and gold risk, respectively. For exchange rate risk (DXY), according to Garman and Klass (1980), we calculate the daily extreme volatility (RV) of the US Dollar Index to represent the exchange rate risk (DXY) using the following formula:

$$RV = 0.511(h-l)^2 - 0.019[(c-o)(h+l-2o) - 2(h-o)(l-o)] - 0.383(c-o)^2 \quad (16)$$

where h, l, o, and c represent the daily high, low, open, and closed prices, respectively. The daily RV is further converted into a percentage of daily annualized volatility using the formula $\delta_t = 100\sqrt{365 \times RV}$, which reflects the USDI volatility of the exchange rate market at each time point. For the bond market index (S&P US Treasury Bond Index), here referring to Corbet (2018), we define the yield as the daily log change and calculate the five-day standard deviation as representing volatility to reflect the volatility of the bond market (BT) at each time point.

Data and descriptive statistics in cryptocurrency markets

Data on cryptocurrencies are obtained from CoinMarketCap,[2] a comprehensive source providing daily high, low, opening and closing prices, along with trading volume and market capitalization of the sampled cryptocurrencies. Price data from CoinMarketCap is calculated based on the weighted average of the prices of all exchange markets for cryptocurrencies, representing the total price of each exchange. As Koutmos (2018) demonstrated, this methodology ensures the validity of the price data used in the empirical analysis. Our analysis focuses on six large cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), XRP, Dogecoin (DOGE), and Litecoin (LTC), whose total market capitalization of these six cryptocurrencies exceeded 1,500 billion USD, accounting for approximately 70% of the total cryptocurrency market capitalization as of January 2, 2022. To capture the expanding diversity and quantity of cryptocurrencies since 2017, our sample period begins on July 28, 2017. This interval encompasses comprehensive data on the six selected cryptocurrencies. After aligning the sample interval with

[2] http://coinmarketcap.com

Table 1 Variable descriptions

Cryptocurrency	Abbrevation	Variable	Data source
Panel A: Cryptocurrency Markets			
Bitcoin	BTC	Daily Bitcoin Price	CoinMarketCap
Ethereum	ETH	Daily Ethereum Price	CoinMarketCap
Binance Coin	BNC	Daily Binance Coin Price	CoinMarketCap
XRP	XRP	Daily XRP Price	CoinMarketCap
Dogecoin	DOGE	Daily Dogecoin Price	CoinMarketCap
Litecoin	LTC	Daily Litecoin Price	CoinMarketCap
Panel B: Uncertainties			
Climate Risk	CLM	Climate Risk Abnormal Google Search Volume Index	Google Trends
Financial Market Risk	FSI	OFR Financial Stress Index	OFR
Policy Risk	EPU	US Economic Policy Uncertainty Index	FRED
International Capital Market Risk	VIX	CBOE Volatility index	Wind
Oil Market Risk	OVX	CBOE Crude Oil Volatility Index	CBOE
Gold Market Risk	GVZ	CBOE Gold ETF Volatility Index	CBOE
Exchange Rate Market Risk	DXY	USD dollar index volatility	Investing.com
Bond Market Risk	BT	S&P U.S. Treasury Bond Index volatility	S&P

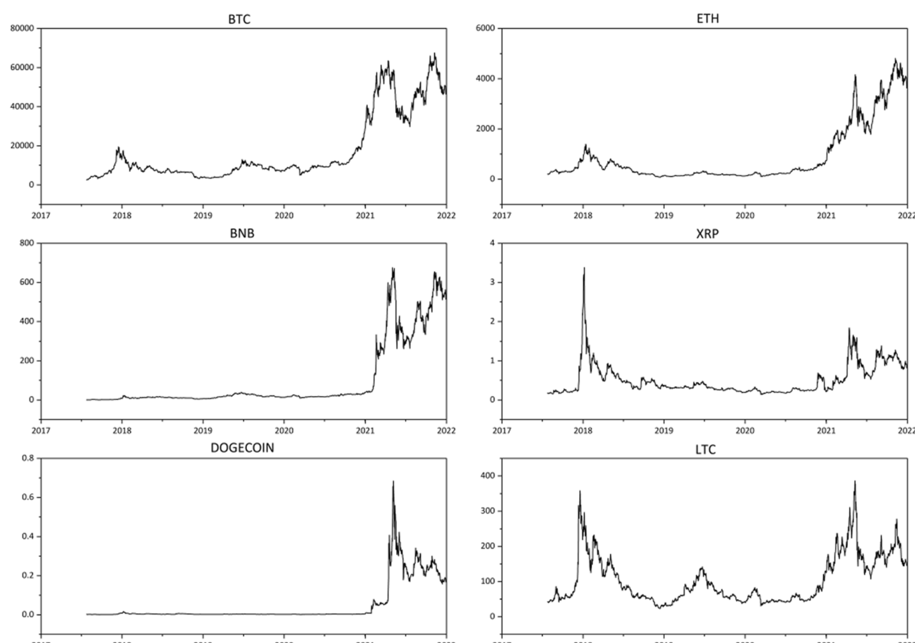

Fig. 1 Daily prices of cryptocurrencies

other market data, we obtain a dataset comprising 1,115 observations on cryptocurrency networks spanning July 28, 2017 to December 30, 2021.

The corresponding variable descriptions are shown in Table 1.

The price trends, correlation figure, and descriptive statistics of the cryptocurrencies are shown in Figs. 1 and 2 and Table 2, respectively. According to the cryptocurrency price data in Fig. 1, there are some similarities in price trends among the

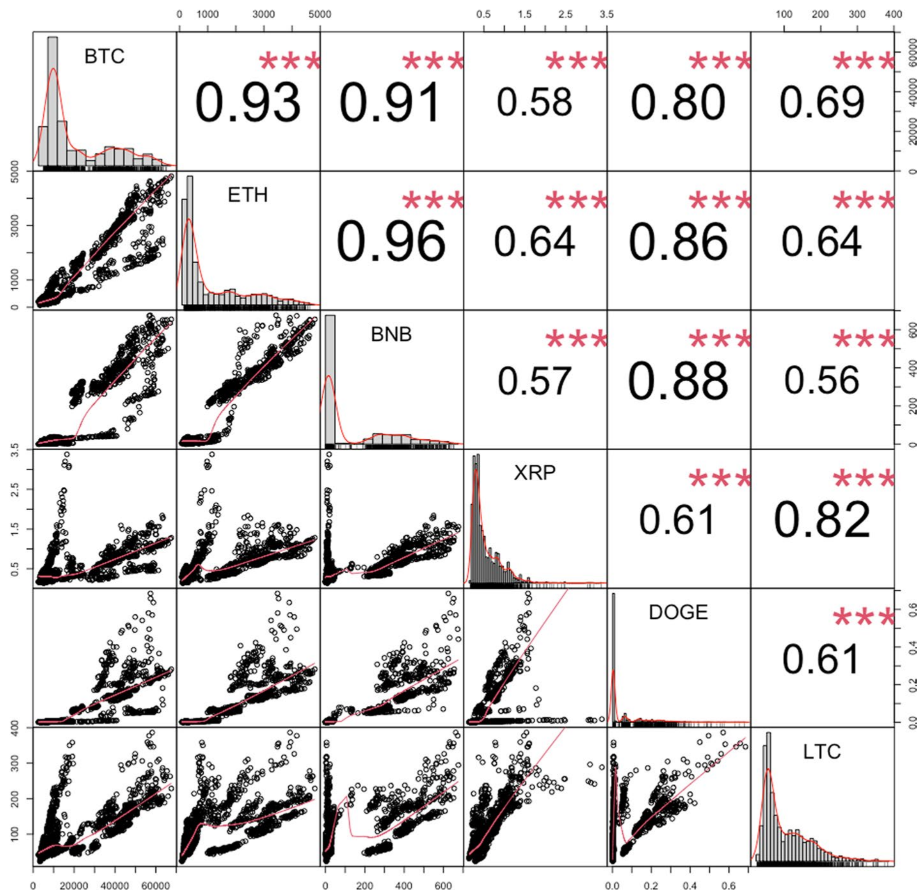

Fig. 2 Cryptocurrency price correlation Note: The diagonal line shows the distribution, the lower-left panel shows the bivariate scatter plot with fitted lines, and the upper-right panel shows the correlation coefficient and significance level

Table 2 Sampling cryptocurrency descriptive statistics

Cryptocurrency	Abbreviation	Average price	Max.price	Min.price	Average volume	Average market Cap
Bitcoin	BTC	19356.1100	67566.8300	2710.6700	24500	358000
Ethereum	ETH	1074.1750	4812.0900	84.3100	12300	124000
Binance Coin	BNC	131.4360	675.6800	0.0999	913	21100
XRP	XRP	0.5123	3.3800	0.1396	2540	22300
Dogecoin	DOGE	0.0564	0.6848	0.0007	955	7370
Litecoin	LTC	100.8915	386.4500	23.4600	2340	6400

Note: The sample period is from July 28, 2017, to December 30, 2021, for all sampled cryptocurrencies. This table lists a sample of six cryptocurrencies by total market capitalization (in descending order) as of January 2, 2022. Columns 2–5 show the abbreviations and average, highest, and lowest prices of cryptocurrencies (in USD), respectively. Columns 6 and 7 show the average trading volume and market capitalization of the cryptocurrencies (in millions of USD), respectively. The sample period is from July 28, 2017, to September 20, 2022, for all sampled cryptocurrencies

various markets, which is also revealed in the correlation depiction in Fig. 2. Among them, Bitcoin and Ethereum had the most similar price volatility characteristics between July 2017 and January 2021. Except for XRP and Litecoin, the rest of the

Table 3 Descriptive statistics of cryptocurrency volatilities

	BTC	ETH	BNB	XRP	DOGE	LTC
Panel A: Upside Risks						
Mean	0.0807	0.1004	0.1257	0.1181	0.1469	0.1085
Median	0.0745	0.0935	0.0992	0.0946	0.1058	0.1006
Maximum	0.3386	0.3715	0.8387	0.7680	2.5424	0.3400
Minimum	0.0098	0.0280	0.0515	0.0508	0.0613	0.0126
Std. Dev	0.0281	0.0270	0.0824	0.0740	0.1349	0.0370
Skewness	3.0897	3.3072	3.3149	3.1015	7.0625	2.1837
Kurtosis	20.4744	22.8718	18.8689	17.3960	98.9210	10.7905
Jarque–Bera	15,960.1800	20,378.4900	13,741.3200	11,415.8500	436,724.7000	3705.7200
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	90.0247	111.9581	140.1729	131.6898	163.7778	120.9835
Sum Sq. Dev	0.8790	0.8117	7.5627	6.0950	20.2829	1.5284
Panel B: Downside Risks						
Mean	− 0.0803	− 0.0996	− 0.1208	− 0.1231	− 0.1492	− 0.1084
Median	− 0.0741	− 0.0929	− 0.0958	− 0.0996	− 0.1025	− 0.1003
Maximum	− 0.0193	− 0.0230	− 0.0519	− 0.0558	− 0.0612	− 0.0150
Minimum	− 0.3266	− 0.3903	− 0.6970	− 0.7730	− 2.8910	− 0.3399
Std. Dev	0.0282	0.0272	0.0770	0.0740	0.1511	0.0370
Skewness	− 3.0937	− 3.5011	− 3.0090	− 3.1015	− 7.4397	− 2.2003
Kurtosis	20.3612	25.5692	15.2211	17.3960	107.3053	10.8902
Jarque–Bera	15,781.7100	25,942.3600	8621.3600	11,415.8500	515,733.2000	3791.9500
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	− 89.5178	− 111.0735	− 134.7417	− 137.2908	− 166.4029	− 120.9185
Sum Sq. Dev	0.8838	0.8219	6.6038	6.0950	25.4409	1.5245

The sample period was from July 28, 2017 to December 30, 2021 for all sampled cryptocurrencies (1,115 daily observations)

markets experienced a relatively flat price change before January 2021. Specifically, the Binance Coin and Dogecoin prices did not change significantly. The Bitcoin and Ethereum market prices experienced some degree of slow growth and retreat from November 2017 to January 2018. Although XRP and Litecoin experienced more significant growth in November 2017 and oscillated back down from December 2017 to February 2018, the price change trends in both markets were similar. All six digital currency prices showed relatively significant growth around the node of January 2021, with greater volatility after that node.

Table 2 presents descriptive data for the six cryptocurrencies. During the sample period, various cryptocurrencies experienced substantial price appreciation, reflecting the volatility of cryptocurrency prices. For example, Bitcoin had a minimum price of $2,710.67 and a maximum price of $67,566.83, and Ethereum had a minimum price of $84.31 and a maximum price of $4,812.09.

Tables 3 and 4 provide the results of the descriptive statistics and correlation matrix for each market volatility (upside risk and downside risk) of cryptocurrencies at the 5% significance level, respectively. As shown in Table 3, in terms of the mean, Dogecoin had the largest upside and downside volatility among the six virtual currencies (0.1469 and -0.1492, respectively). Bitcoin had relatively less volatility in both directions (0.0807 and -0.0803, respectively). According to the results presented in

Table 4 Cryptocurrency volatility correlation matrix

	BTC	ETH	BNB	XRP	DOGE	LTC
Panel A: Upside Risks						
BTC	1.0000	0.7578	0.4699	0.4647	0.3085	0.6105
ETH	0.7578	1.0000	0.4015	0.5217	0.3377	0.6765
BNB	0.4699	0.4015	1.0000	0.3971	0.2700	0.4356
XRP	0.4647	0.5217	0.3971	1.0000	0.4635	0.5852
DOGE	0.3085	0.3377	0.2700	0.4635	1.0000	0.3537
LTC	0.6105	0.6765	0.4356	0.5852	0.3537	1.0000
Panel B: Downside Risks						
BTC	1.0000	0.7573	0.4932	0.4649	0.2758	0.6155
ETH	0.7573	1.0000	0.4557	0.4855	0.2839	0.6602
BNB	0.4932	0.4557	1.0000	0.4085	0.2376	0.4694
XRP	0.4649	0.4855	0.4085	1.0000	0.4480	0.5802
DOGE	0.2758	0.2839	0.2376	0.4480	1.0000	0.3165
LTC	0.6155	0.6602	0.4694	0.5802	0.3165	1.0000

The sample period was from July 28, 2017, to December 30, 2021, for all sampled cryptocurrencies (1,115 daily observations)

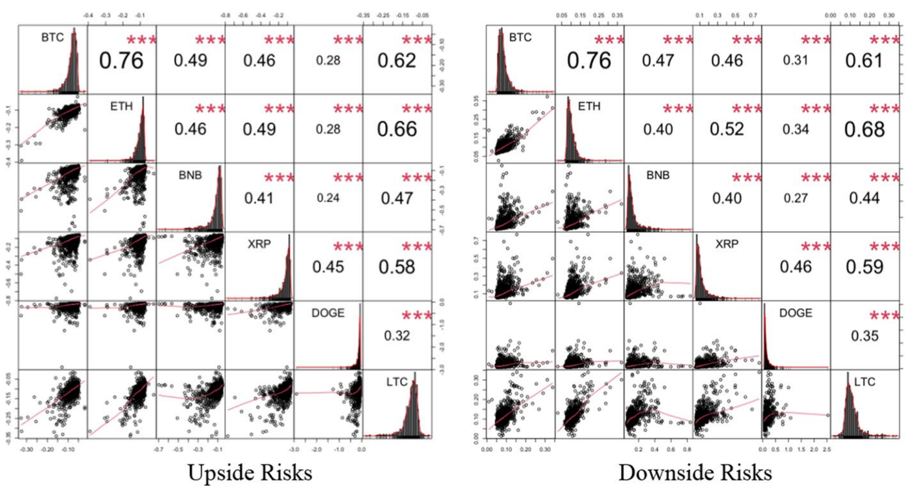

Fig. 3 Correlation description of the upside risk and downside risk in cryptocurrency markets

Table 4A and B, Bitcoin had the highest volatility correlation with Ethereum at both upside and downside risk levels (0.7578 and 0.7573, respectively). This was followed by Ethereum and Litecoin (0.6765 and 0.6602, respectively). The volatility correlations between cryptocurrencies are consistent with the changes in the price trend graph.

Fig. 3 shows the correlations of extreme risks for each type of cryptocurrency. As shown in Fig. 3, for both types of risk, BTC and ETC have the highest correlation, which corresponds to the strong price volatility correlation shown in Fig. 2. BNB and DOGE have the lowest volatility correlation for upside and downside risks, and although they show a high correlation in price trends, the spreads of extreme risk changes in the two markets are less consistent.

Table 5 Descriptive statistics of various market uncertainties

	CLM	EPU	FSI	VIX	OVX	GVZ	USDI	BT
Mean	0.00	0.08	0.00	0.01	0.01	0.00	6.18	0.03
Median	0.02	− 0.63	− 0.02	− 0.13	− 0.14	− 0.05	5.74	0.03
Maximum	4.00	358.28	3.45	24.86	130.22	7.25	29.35	0.25
Minimum	− 3.52	− 308.95	− 1.58	− 17.64	− 90.61	− 9.50	0.00	0.00
Std. Dev	1.00	64.64	0.28	2.32	7.55	1.01	2.78	0.02
Skewness	0.11	0.07	3.75	2.71	3.89	0.03	2.19	4.51
Kurtosis	4.26	5.98	42.91	32.65	145.42	18.82	13.68	34.54
Jarque–Bera	75.67	413.20	76,616.61	42,206.01	945,195.00	11,632.51	6192.18	49,998.28
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	1.40	91.18	1.21	7.22	10.39	3.53	6896.27	36.56
Sum Sq. Dev	1115.98	4,655,124.00	86.67	6000.58	63,555.77	1132.21	8630.81	0.52

The sample period was from July 28, 2017 to December 30, 2021 for all sampled cryptocurrencies (1,115 daily observations)

Table 6 Cryptocurrency unit root test results

	Upside risk test statistic	Downside risk test statistic
BTC	− 5.6903***	− 5.7308***
ETH	− 7.2362***	− 7.0445***
BNB	− 5.8829***	− 5.1337***
XRP	− 7.2644***	− 7.2644***
DOGE	− 12.4004***	− 12.1477***
BTC	− 6.1637***	− 6.0747***

*** denotes significance at the 1% level; the ADF test for the unit root in level, including the intercept term, was used for the unit root test, where the lag length was automatically selected using the Schwarz information criterion (maximum lags: 24)

Data and descriptive statistics of uncertainties

After excluding non− trading day data, a complete set of 1,115 observations is obtained, encompassing the networks that encompassed extreme risks in the cryptocurrency market and various market uncertainties. The data collection period spans from July 28, 2017 to December 30, 2021. The sample data interval covers events that had a significant impact on the stability of each market, such as the US–China trade war in 2018, the sharp decline in oil prices in 2019, the global COVID− 19 pandemic in 2020, and the subsequent global supply chain crisis in 2021. As shown in Table 5, the crude oil market (OVX), climate shocks (CLM), and policy (EPU) had the highest volatility from a standard deviation over the mean perspective, followed by the gold market (GVZ), international capital markets (VIX), and financial markets (FSI). The exchange rate (USDI) and bonds (BT) markets are less volatile.

Empirical analysis

Connectedness network analysis in cryptocurrency markets

Augmented Dickey Fuller (ADF) and box test

First, we established a dynamic risk spillover network for cryptocurrency markets based on TVP-VAR. According to the results of the unit root test in Table 6, the time

Table 7 Cryptocurrency volatility Box–Pierce and Box–Ljung test results

	Box-Pierce test		Box-Ljung test	
	X-squared	df	X-squared	df
Panel A: Upside Risks				
BTC	2066.4***	5	3057.7***	10
ETH	2215.3***	5	2590.3***	10
BNB	3492.2***	5	5299.5***	10
XRP	1959.9***	5	2845.7***	10
DOGE	1065.9***	5	1267.8***	10
LTC	2414.0***	5	3456.0***	10
Panel B: Downside Risks				
BTC	2082.5***	5	3070.1***	10
ETH	2240.7***	5	2601.3***	10
BNB	3545.5***	5	5360.6***	10
XRP	1959.9***	5	2845.7***	10
DOGE	1152.4***	5	1360.0***	10
LTC	2418.6***	5	3460.6***	10

Note: *** denotes significance at the 1% level

series of the six cryptocurrency volatilities (upside and downside risks) are all stationary at the 1% confidence level. The results of the Ljung–Box and Pierce–Box tests show that all series are significantly autocorrelated at the 1% level and that the series are not white noise series, as shown in Table 7. Therefore, a TVP-VAR model with time-varying variances can be used to effectively model the dynamic connectivity between the two types of risks in the cryptocurrency market.

Dynamic connectedness network

Based on the daily upside and downside volatility data series of six cryptocurrencies (Bitcoin, Ethereum, Binance Coin, XRP, Dogecoin, and Litecoin) for a total of 1,115 observations from July 28, 2017 to September 20, 2022, dynamic connectivity networks of upside and downside risks based on TVP-VAR models were established. According to the HQ and SC information criteria, the lag orders of the upside and downside risk VAR models were both six, and the variance decomposition period $H=7$ (i.e., seven-day forward prediction) was chosen to obtain the results.

Considering the temporal scale of our model, we consider long- and short-term risk transmission and their economic and financial implications. The static results obtained from the complete sample are more suitable for long-term risk management, whereas the dynamic results are more applicable for short-term risk management.

1. Static Analysis of Risk Spillover Effect

Statically, Table 8A and B provide a complete sample analysis of the upside and downside volatility spillovers predicted for the previous seven periods. Column i represents the shock of cryptocurrency i to other currencies (TO) and row j represents the shock of cryptocurrency j to other currencies (FROM). The spillover index, TCI,

Table 8 Spillover table for cryptocurrency extreme risks (upside risks and downside risks)

	BTC	ETH	BNB	XRP	DOGE	LTC	FROM
Panel A: Upside Risks							
BTC	45.93	18.46	8.80	9.21	8.26	9.35	54.07
ETH	17.43	39.90	9.08	11.57	9.13	12.88	60.10
BNB	11.76	8.48	50.30	12.62	10.00	6.84	49.70
XRP	9.58	10.09	9.88	49.33	12.68	8.43	50.67
DOGE	6.14	5.17	9.47	13.67	60.13	5.42	39.87
LTC	16.6	12.59	7.53	10.97	9.06	43.24	56.76
TO	61.51	54.78	44.76	58.04	49.14	42.93	311.16
Inc.Own	107.44	94.68	95.06	107.38	109.27	86.18	TCI
NET	7.44	-5.32	− 4.94	7.38	9.27	− 13.82	51.86
Panel B: Downside Risks							
BTC	45.6	17.29	10.55	10.11	7.46	9.00	54.40
ETH	16.36	37.90	12.77	12.65	8.35	11.96	62.10
BNB	9.40	8.53	51.68	12.89	10.42	7.09	48.32
XRP	9.47	8.79	10.29	49.73	14.54	7.18	50.27
DOGE	5.70	5.76	8.84	14.35	61.41	3.94	38.59
LTC	15.59	12.29	9.42	10.86	7.59	44.25	55.75
TO	56.52	52.65	51.87	60.87	48.36	39.16	309.43
Inc.Own	102.12	90.55	103.54	110.6	109.77	83.41	TCI
NET	2.12	-9.45	3.54	10.60	9.77	-16.59	51.57

is provided in the lower-right corner of the upside volatility (Panel A) and downside volatility (Panel B).

Table 8A shows that the TCI for upside risk in the six cryptocurrency markets was 51.8%, indicating that 51.8% of the extreme risk in the cryptocurrency markets came from volatility spillovers between the respective markets, except for the individual submarkets themselves, whereas the remaining 48.2% came from shocks in the respective markets themselves. The downside risk spillover in Table 8B provides findings consistent with those of the upside risk. First, the spillover index was 51.57% (0.23% lower than the upside risk). Second, the XRP, Dogecoin, Binance Coin, and Bitcoin markets had large directional spillovers to other markets, with all showing a net spillover effect. However, for the Ethereum and Litecoin markets, the net spillover indices were negative, indicating that these two markets were more exposed to risk spillover from the other markets (Bitcoin, Binance Coin, XRP, and Dogecoin).

In terms of the total directional connectedness from others (FROM), Ethereum received the highest spillover from others (60.1% for upside and 62.1% for downside), while Dogecoin had the lowest FROM (39.87% for upside and 38.59% for downside). This indicates that the Dogecoin market itself had a strong ability to process and obtain information, and the adjustment speed was faster after being disturbed by external market information. Dogecoin's transaction process is based on the Scrypt algorithm, which has a faster confirmation time than Bitcoin transactions. Viewed from the total directional connectedness TO, Bitcoin was the main contributor to the remaining cryptocurrencies' shocks, with 61.51% and 56.52% of the upside and downside spillover indexes, respectively, and with both the net directional connectedness indexes being positive. As the earliest issued cryptocurrency with the largest trading volume and market capitalization,

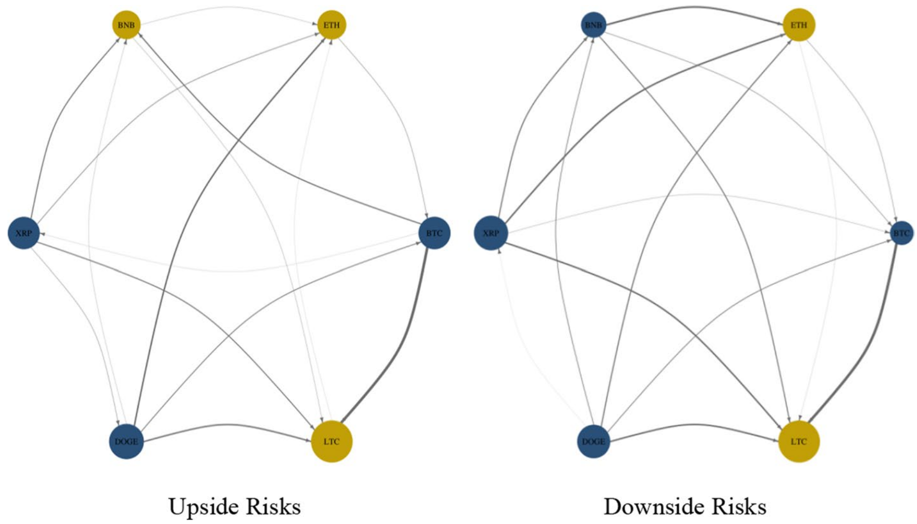

Fig. 4 Cryptocurrency directional volatility connectedness network over the full sample

Bitcoin's market is more developed and has more information-processing power relative to other cryptocurrencies. It is in a dominant position in terms of risk transmission and can generate risk spillovers to other markets through changes in the market environment and information transmission. Bitcoin's dominant role was followed by XRP, with upside and downside spillovers to others reaching 58.04% and 60.87%, respectively, showing positive net total directional connectedness. However, the Litecoin market is more influenced by other markets relative to itself, despite its small trading volume(Ji et al. 2019a). The upside risk and downside risk spillovers were both minimal (42.93% and 39.16%, respectively) and were more subject to risk spillover from other markets.

Figure 4 shows the NPDC of the six cryptocurrency markets. The size of the nodes indicates the magnitude of the net spillover index, and the blue and yellow nodes represent markets with positive and negative net spillover indices, respectively. The arrows of the two markets point to markets with a lower spillover than another market's spillover to them. The market with more arrows pointing toward it possesses less self-explanatory power than other markets and behaves as a net recipient of spillover effects. The thickness of the arrows represents the strength of the net pairwise risk spillover.

As illustrated in Fig. 4, the markets of XRP, Dogecoin, and Bitcoin are characterized by blue nodes, signifying their position as net transmitters within the network. In contrast, the Binance Coin market has undergone a notable transformation from being a net risk recipient in upward risk to assuming the role of a net risk transmitter in downward risk. The Ethereum and Litecoin markets are represented by yellow nodes, with the highest number of arrows pointing towards them in upside and downside risks, indicating that these two cryptocurrencies had weaker explanatory power relative to other currencies and were more susceptible to risk spillovers from other markets. Furthermore, as the largest yellow node in the network, the Litecoin market exhibits a negative and minimal net spillover index, indicating that it serves as a net recipient of risk spillover and has a relatively weaker explanatory power of its own. These results correspond to the spillover results for extreme cryptocurrency risks shown in Table 8. Taking upside risk as an

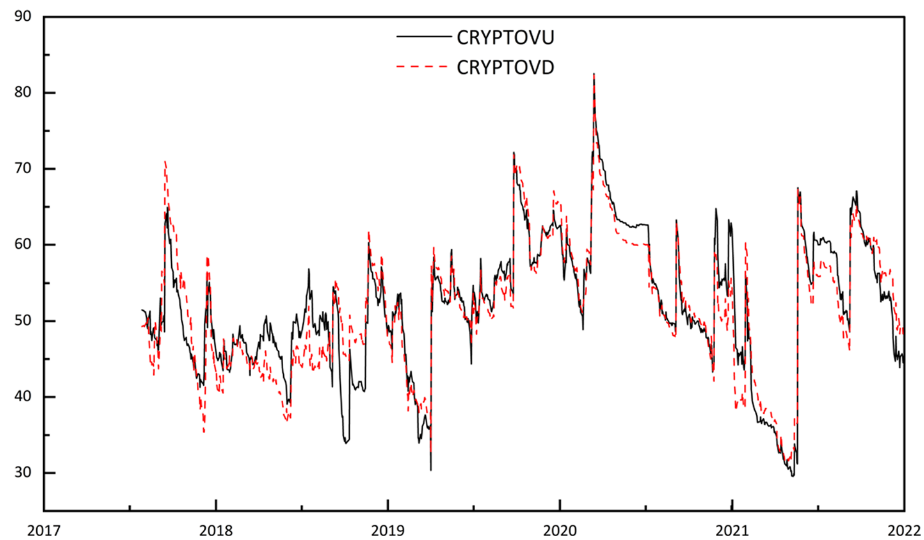

Fig. 5 Dynamic total connectedness index of cryptocurrency upside and downside risk networks based on a TVP-VAR model

example, Bitcoin's spillover index value to Ethereum alone was 17.43%, and Ethereum's spillover index value to Bitcoin was 18.46%, indicating that there was a clear two-way risk spillover effect between the two markets, that is, Bitcoin and Ethereum, with consistent results for downside risk. Similarly, there was a significant two-way risk spillover between the Litecoin and Bitcoin markets (18.39% and 19.42%, respectively). However, there was some asymmetry in the risk spillover between Bitcoin and Litecoin (16.6% for Bitcoin to Litecoin and 9.35% for the reverse). In addition, when analysing the spillover indices of volatility between the Ethereum market and any other market, the Ethereum market showed that the risk spillover from other markets was stronger than its own risk spillover to other markets.

2. Dynamic Analysis of Risk Spillover Effects

Figure 5 shows how the interdependence among the six cryptocurrencies changed over time, which has been done by using the constructed TCIs, which represent the cryptocurrency extreme risks (CRYPYPVU and CRYPTOVD represent upside risk and downside risk, respectively). The two indices will be used in the second TVP-VAR-DY connectedness network as the uncertainties in cryptocurrency markets. Here, the TCI of the upside risk and downside risk had similar spillover magnitudes within the overall sample and maintained a narrow spread (i.e., they exhibited more synchronized movement overall). This result was consistent with those for both risks, as shown in Table 8. Specifically, the total spillover index for both extreme risks increased sharply in response to an extreme global event. After the COVID-19 pandemic outbreak in 2020, the overall exposure across markets showed a rapid expansion trend, with the TCI growing to 80%.

Figure 6 shows the net pairwise transmission of the cryptocurrency market, illustrating the number of sequences that dominate the other sequences in the network. The number of other markets dominated by Bitcoin, XRP, and Dogecoin was higher throughout the entire sample period, while quantitatively, the dominant role of the Litecoin market in other

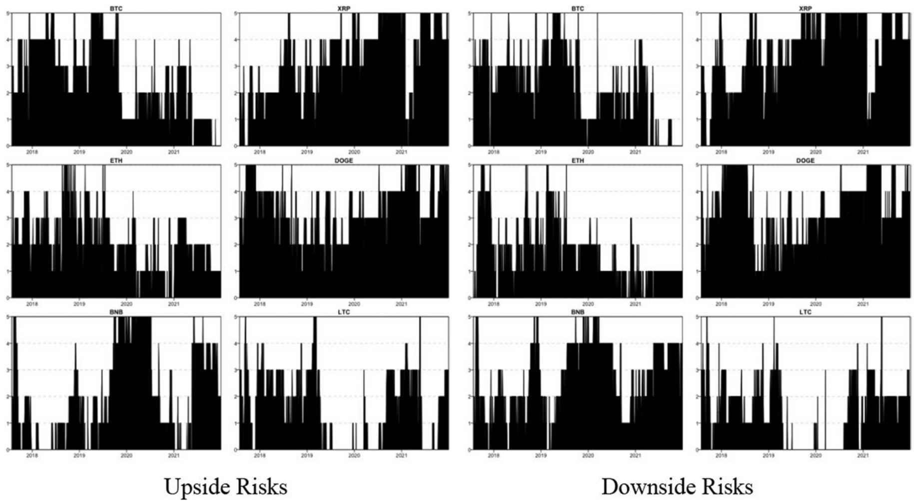

Fig. 6 Net pairwise transmission (NPT) in cryptocurrency markets Note: This figure summarizes the net transmission mechanisms for each series. The cryptocurrency market risk spillover network comprises six series, each of which dominates up to five

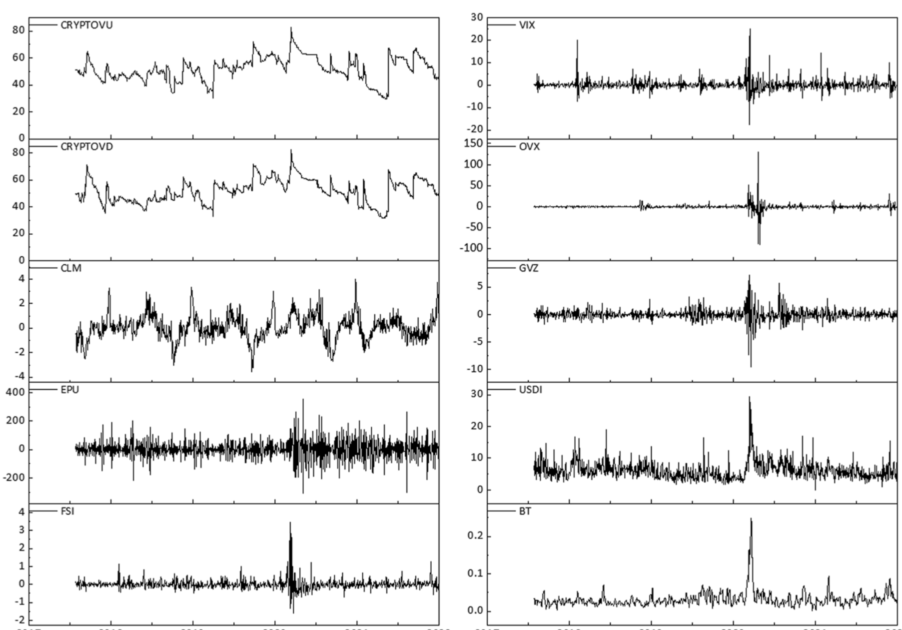

Fig. 7 Dynamic volatility of each market

markets was weaker. Binance Coin had a certain variation for risk transmission to other markets in the interval—specifically, the dominant role was stronger between September 2019 and January 2021 up to five sequences. During the remaining period, the XRP market played a weaker role in risk transmission to other markets.

Connectedness network analysis of the cryptocurrency market and other uncertainties

Time-varying volatility characteristics of each market

Excluding non-trading daily data, a total of 1,115 observations were obtained for the period of July 28, 2017, to December 30, 2021. Figure 7 presents a time trend graph of the volatility for each market.

Figure 7 shows some similarities in the volatility characteristics between the various markets. The volatility characteristics of the cryptocurrency market were relatively similar to the financial market (FSI) and international capital market (VIX), and the cryptocurrency market was somewhat like the gold market (GVZ) and crude oil market (OVX). In addition, each market had more dramatic volatility (spikes and plunges) after the COVID-19 outbreak in 2020, reflecting its impact of the COVID-19 outbreak on the stability of each market.

Table 9 presents the results of the descriptive statistics and correlation matrix for each market volatility. The cryptocurrency market had the highest correlation (0.93) for upside risk and downside risk because of the calculation method. The volatility correlation between the international capital market (VIX) and financial market (FSI) was significant at 0.74. In addition, the volatility correlation between the financial market (FSI), crude oil market (OVX) and gold market (GVZ) was significant. For the cryptocurrency market, its volatility was highly correlated with the volatility of the bond market (BT), and the fluctuations were strongly influenced by climate change, with a negative relationship with the volatility of the financial market (FSI) and international capital market (VIX).

ADF and box test

All series were stationary at the 5% confidence level, according to the ADF test (Table 10). The Ljung–Box and Pierce–Box test results show that all series were significantly autocorrelated at the 1% level, and the series were not white noise. Table 11 presents the autocorrelation test results. The sequences were all stationary and could be modelled using a TVP-VAR model with time-varying variances (TVP-VAR).

Dynamic connectedness network analysis

A total of 1115 observations of cryptocurrency market extreme risk volatility (upside and downside) with daily volatility data series of climate shocks and other uncertainties from the trading days of July 28, 2017 to December 30, 2021 were included in the analysis to build a dynamic connectedness network based on the TVP-VAR model.

1. Static Analysis of Risk Spillover Effects

As shown in Table 12, the results of static connectedness suggested that the TCI for all markets was 43.25%. In addition to each variable itself, 43.25% of the overall market's risk came from the spillover effect between each individual market. Among them, cryptocurrency upside risk and downside risk showed positive net total directional connectedness (4.14% and 0.05%, respectively), with the dominant effect of upside risk being stronger than the downside risk. Overall, the climate risk exhibited a net spillover

Table 9 Correlation analysis of various market uncertainties

	CRYPTOVU	CRYPTOVD	CLM	EPU	FSI	VIX	OVX	GVZ	USDI	BT
CRYPTOVU	1.0000	0.9275	0.1173	0.0031	−0.0096	−0.0260	0.0135	0.0075	0.0858	0.3048
CRYPTOVD	0.9275	1.0000	0.0217	0.0032	0.0003	−0.0235	0.0184	0.0131	0.0570	0.3015
CLM	0.1173	0.0217	1.0000	0.0487	0.0078	−0.0116	−0.0047	0.0231	0.1089	0.0979
EPU	0.0031	0.0032	0.0487	1.0000	−0.0080	−0.0429	0.0350	0.0135	0.0221	0.0267
FSI	−0.0096	0.0003	0.0078	−0.0080	1.0000	0.7438	0.3413	0.4027	0.1312	0.1067
VIX	−0.0260	−0.0235	−0.0116	−0.0429	0.7438	1.0000	0.2500	0.3530	0.0721	0.0246
OVX	0.0135	0.0184	−0.0047	0.0350	0.3413	0.2500	1.0000	0.1904	0.0374	0.0822
GVZ	0.0075	0.0131	0.0231	0.0135	0.4027	0.3530	0.1904	1.0000	0.0341	0.0063
USDI	0.0858	0.0570	0.1089	0.0221	0.1312	0.0721	0.0374	0.0341	1.0000	0.3858
BT	0.3048	0.3015	0.0979	0.0267	0.1067	0.0246	0.0822	0.0063	0.3858	1.0000

Table 10 ADF test results

	t-statistic	Prob
CRYPTOVU	− 4.3649***	0.0004
CRYPTOVD	− 4.5967***	0.0001
CLM	− 5.1572***	0.0000
EPU	− 21.848***	0.0000
FSI	− 8.6417***	0.0000
VIX	− 18.321***	0.0000
OVX	− 13.778***	0.0000
GVZ	− 34.634***	0.0000
USDI	− 6.8665***	0.0000
BT	− 7.6330***	0.0000

*** denotes significance at the 1% level. The ADF test for the unit root in level, including the intercept term, was used for the unit root test, where the lag length was automatically selected via the Schwarz information criterion (maximum lags: 24)

Table 11 Box–Pierce and Box–Ljung test results

	Box-Pierce test		Box-Ljung test	
	X-squared	df	X-squared	df
CRYPTOVU	4585.10***	5	7921.40***	10
CRYPTOVD	4551.50***	5	7832.70***	10
CLM	2665.00***	5	4127.50***	10
EPU	261.37***	5	274.91***	10
FSI	66.95***	5	104.62***	10
VIX	98.21***	5	135.59***	10
OVX	77.80***	5	136.22***	10
GVZ	13.26***	5	44.12***	10
USDI	905.79***	5	1425.40***	10
BT	3091.30***	5	4095.90***	10

*** denotes significance at the 1% level

effect. In addition, four markets—finance, international capital, crude oil, and gold—had large outward spillovers and showed net total directional connectedness (15.02%, 8.21%, 3.55%, and 0.29%, respectively). For the three uncertainties—policy, exchange rate, and bonds—the impact of the shocks on the other markets was weak, and the net spillover index was negative (− 5.23%, − 5.3%, and − 23.48%, respectively).

According to Table 12, the total directional connectedness FROM others indicates that financial markets were exposed to the largest risk spillover (56.24%) and that climate shocks were affected by the smallest risk spillover (20.92%) of the whole interval. The larger the FROM value, the slower the price adjustment to the deviations from the expected market value after being disturbed by external market information, indicating that the market itself had a relatively weak capacity to acquire and process information. From the total directional connectedness TO others, the financial market (71.26%) and international capital market (60.25%) had the strongest risk spillover effects, indicating that these two markets were strongly correlated with the global economic cycle and could generate risk spillover to other markets through changes in the economic environment.

Table 12 Full sample static connectedness table for cryptocurrency market and other uncertainties

	CRYPTOVU	CRYPTOVD	CLM	EPU	FSI	VIX	OVX	GVZ	USDI	BT	FROM
CRYPTOVU	51.48	38.04	2.10	1.09	1.39	1.31	1.23	1.17	1.05	1.13	48.52
CRYPTOVD	38.64	48.85	2.83	1.12	1.77	1.50	1.57	1.25	1.40	1.06	51.15
CLM	2.36	2.01	79.08	3.26	2.31	1.77	2.91	2.74	1.89	1.66	20.92
EPU	1.74	1.48	3.72	77.28	3.92	2.08	3.11	2.91	2.06	1.70	22.72
FSI	1.14	1.17	1.95	1.61	43.76	28.61	8.23	10.09	2.22	1.22	56.24
VIX	0.81	0.62	1.35	1.21	29.41	47.95	6.18	9.00	2.40	1.07	52.05
OVX	0.95	0.90	2.55	2.19	10.53	7.78	65.2	6.62	2.20	1.09	34.80
GVZ	1.45	1.65	2.84	2.42	12.24	10.12	6.18	59.79	2.00	1.33	40.21
USDI	2.35	2.68	3.48	2.51	3.41	2.68	4.73	2.32	73.47	2.37	26.53
BT	3.20	2.66	2.87	2.09	6.28	4.40	4.20	4.40	6.00	63.89	36.11
TO	52.66	51.19	23.69	17.49	71.26	60.25	38.35	40.50	21.22	12.62	389.24
Inc.Own	104.14	100.05	102.77	94.77	115.02	108.21	103.55	100.29	94.7	76.52	TCI
NET	4.14	0.05	2.77	− 5.23	15.02	8.21	3.55	0.29	− 5.30	− 23.48	38.92
NPT	6	4	5	2	9	8	6	4	1	0	

The reported values are variance decompositions based on the TVP-VAR model. A lag order of three has been chosen according to the HQ information criterion, and the variance decomposition period H = 7 has been chosen (i.e., a prediction of seven trading days forward) to obtain static connectedness results for all markets

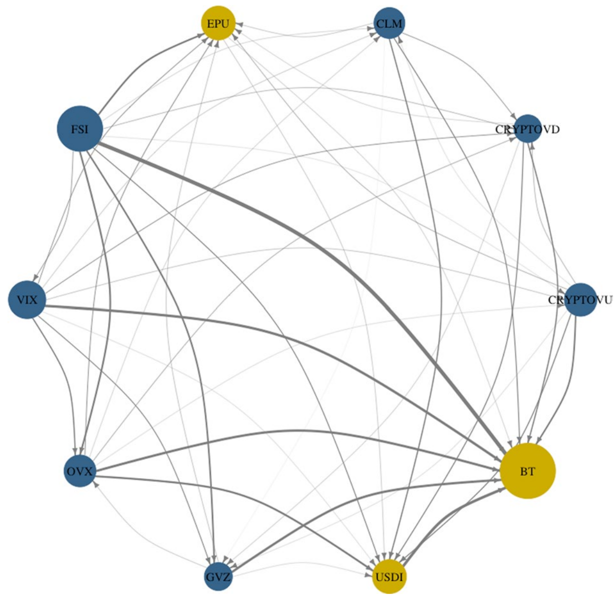

Fig. 8 Directional volatility connectedness network over the full sample (threshold = 0.01) Note: The blue nodes represent markets with positive net spillover indices, indicating their role as net risk transmitters. The yellow nodes represent markets with negative net spillover indices, indicating their role as net risk recipients. The node size reflects the magnitude of the absolute value of the net spillover index. The arrows of the two markets point to markets with a lower spillover than another market's spillover to them. A market with more arrows pointing toward it possesses less self-explanatory power than other markets and behaves as a net recipient of spillover effects. The thickness of the arrows represents the strength of net pairwise risk spillovers

Figure 8 represents the pairwise directional volatility connectedness network. Based on the color and size of the nodes, the bond, exchange rate, and policy market nodes are characterized by yellow, denoting their status as net risk recipients within the network. Among these, the bond market has the largest node size, indicating a relatively weak explanatory power. Conversely, the uncertainty nodes of other markets are represented in blue, signifying their roles as net risk transmitters in the network. Notably, the financial market displays the highest net spillover index and possesses the largest node size. In addition, most arrows point towards policy factors, exchange rate markets, and bond markets. These three markets had weaker explanatory strengths relative to other markets and were more susceptible to risk spillovers from other markets. For the cryptocurrency market, the volatility of both the upside and downside risks pointed to policy factors: the exchange rate, bond, and gold markets. However, downside risk had greater spillover to the gold market, with the downside risk of unsupported cryptocurrency prices affecting the volatility of the gold market more. The NPDC of climate shocks to downside risk in the cryptocurrency market was greater, with the arrow pointing to the cryptocurrency market, indicating the dominance of climate risk in the risk transmission between the two markets, and the more significant impact of climate shocks on cryptocurrency price declined.

Figure 9 shows the risk spillovers "FROM" other markets and "TO" other markets for cryptocurrency upside risks and cryptocurrency downside risks. Figure 10 shows the risk spillovers from climate risk "TO" other markets. For the cryptocurrency market, the total directional connectedness from others for upside risk and downside risk reached

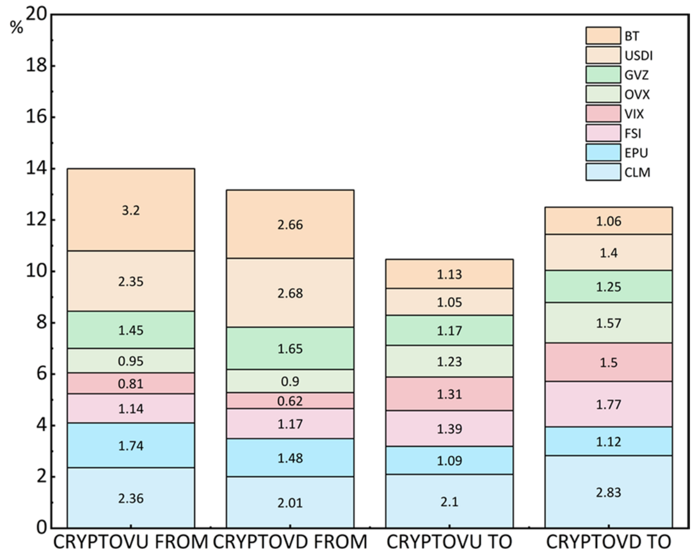

Fig. 9 Risk spillover "FROM" and "TO" others for upside risks CRYPTOVU and downside risks CRYPTOVD
Note: This figure shows the risk spillover FROM and TO other markets in the network for the cryptocurrency markets' upside and downside risks, excluding the cryptocurrency markets themselves. The first and second columns present the risk spillovers from other markets for cryptocurrency upside and downside risks, respectively. The third and fourth columns present the risk spillovers to other markets for cryptocurrency upside and downside risks, respectively

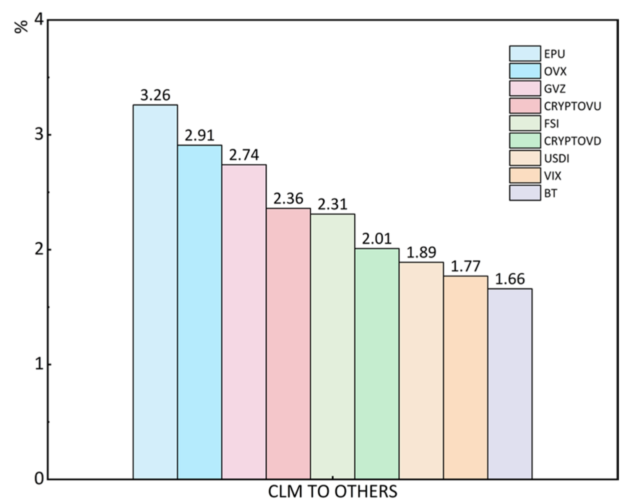

Fig. 10 Risk spillover from climate risks "TO" other markets Note: This figure shows risk spillovers from climate risk to other markets

48.52% and 51.15%, respectively, and the risk spillover to others reached 52.66% and 51.19%, respectively. The directional connectedness in both directions (FROM and TO) ranked in the middle of each market, and the influence of the cryptocurrency's upside and downside risks on the analyzed network were both positive (4.14% and 0.05%, respectively). First, regarding upside risk, the cryptocurrency market was the most sensitive to changes in climate risk volatility (2.1%), followed by the financial and international capital markets (1.31% and 1.31%, respectively), except for downside risk. The cryptocurrency market was relatively less sensitive to changes in exchange rate volatility and policy factors (1.05% and 1.09% for spill-in risk, respectively). In terms of risk spillover TO, the cryptocurrency market had the highest intensity of risk spillover to the bond market (3.2%), reflecting the fact that the cryptocurrency market affected the volatility of the bond market to some extent. For the cryptocurrency market downside risk, the directional connectedness results were consistent with the upside risk. It is also notable that the downside risk was subject to a larger risk spillover from the crude oil market (1.57%), and the volatility of the crude oil market affected the cryptocurrency market price's downside risk to a greater extent.

As shown in Figs. 9 and 10, there was an exposure correlation between cryptocurrency markets and climate risk but with slight differences in both directions of cryptocurrency market upside risk and downside risk. Specifically, the risk spillover from climate risk to downside risk (2.83%) was slightly higher than the shock to upside risk (2.1%), and the risk transmission from climate shocks to the cryptocurrency market downside risks (i.e., unsupported declines) was stronger than the risk transmission to cryptocurrency market upside risks (i.e., uncertain increases). In terms of the intensity of risk spillovers from climate risk to other markets, as shown in Fig. 10, climate shocks had the largest spillover effects on policy uncertainty, as well as exchange rate markets (3.72% and 3.48%, respectively), which may be interpreted as climate risk generating risk transmission to other markets through its impacts on investor attention and policy changes. Climate risk also affected the bond, gold, and cryptocurrency market downside risk, as well as the cryptocurrency market upside and crude oil market volatility to a great extent. In contrast, climate shocks have a relatively low risk correlation with financial and international capital markets. The corresponding strength of total directional connectedness from others (FROM) reflects the sensitivity of climate risk to volatility in other markets. In addition to the risk spillover from policy uncertainty (3.26%), climate risk was also more sensitive to volatility in the crude oil market uncertainty (2.91%). The volatility of the crude oil market, on the one hand, affected public expectations and concerns about climate change; on the other hand, the large amount of greenhouse gases generated by energy-related economic activities had a direct impact on climate change. In this study, climate risk was also affected by gold market volatility, which bore a risk spillover intensity of 2.74%.

When examining the strength of risk spillovers between the various submarkets, the financial and international capital markets exhibited high risk connectedness, with the two taking each other's risk spillover, accounting for approximately 50% of their total risk spillover based on the analyzed network. Moreover, the financial and gold markets were more sensitive to each other's volatility changes, and the intensity of the risk premium from each other's market was 12.24% and 10.09%, respectively. The risk spillover was somewhat asymmetric, and the risk spillover from the financial market to the gold market was greater (more than 2.15%). As gold tends to be regarded as a common liquidity reserve and hedge asset, when the stock market was more volatile, the flow of funds into the gold market to the hedge increased, and there was a stronger risk spillover between the two markets. In addition, the risk connectedness between the financial market and crude oil market was also greater and slightly lower than that of the gold market, and the strength of the risk spillover that the two markets bore from one another was 10.53%

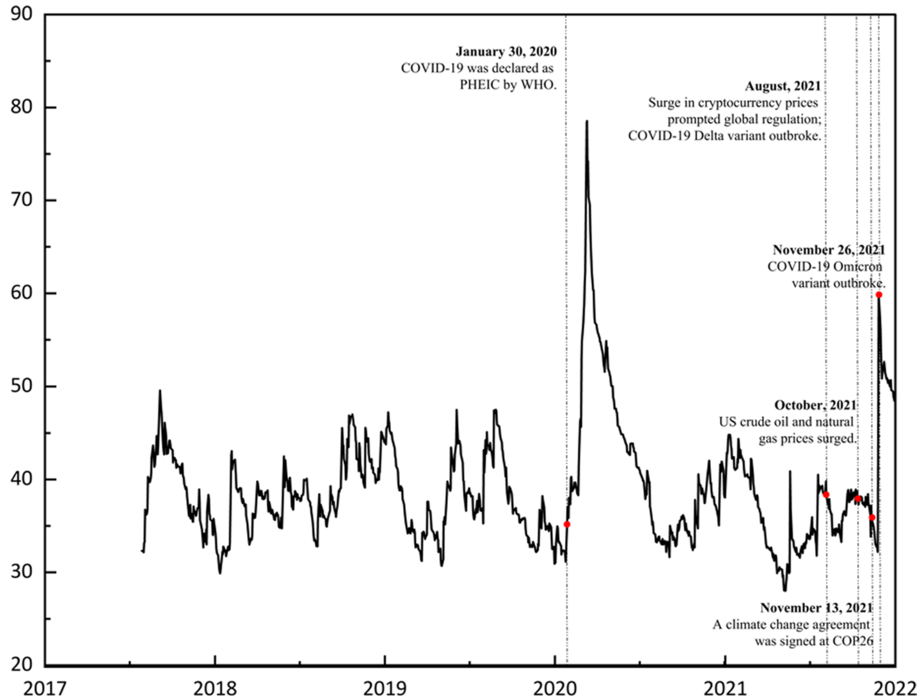

Fig. 11 Dynamics of the total connectedness index of the markets based on the TVP-VAR model

and 8.23%, respectively. Specifically, the strength of risk spillovers from financial market uncertainty to policy uncertainty, exchange rate market uncertainty, and bond market uncertainty was higher (3.92%, 3.41%, and 6.28%, respectively), while the strength of risk spillovers from policy uncertainty, exchange rate market uncertainty and bond market uncertainty to financial market uncertainty was smaller (1.61%, 2.22%, and 1.22%, respectively). The risk spillover effects of international capital market uncertainty on policy uncertainty, exchange rate market uncertainty, and bond market uncertainty corresponded to those of the financial markets. Policy uncertainty, exchange rate market uncertainty and bond market uncertainty were reflected as being mainly influenced by the financial market and the international capital market in the process of risk transmission, bearing more information shocks from the external market.

2. Time-Varying Fluctuation Spillover Effect Analysis

Because a static spillover analysis entails the value obtained by averaging the spillover indices over the entire interval, it is difficult to reflect the fluctuations and changes in different phases. Furthermore, the time-varying volatility analysis of the risk spillover effects was more applicable to risk management over shorter periods. According to the TCI shown in Fig. 11, the total spillover effects of the overall market varied in a range of 30% to 50% from July 2017 to January 2020. On January 30, 2020, the World Health Organization (WHO) issued the highest-level alert, officially declaring COVID-19 as a public health emergency of international concern (PHEIC). The TCI increased significantly under the impact of the extreme event, showing a surge from January 2020 to March 2020 and a peak of 78.41% during this period on March 9, 2020.

From March 2020 to September 2020, the total risk connectedness showed an oscillating downward trend, with some fluctuations, but an overall downward trend. In this phase of relatively stable global economic, political, and COVID-19 pandemic normalization, investors' risk aversion decreased and risk spillovers gradually fell. The index has maintained a smaller rate of change since October 2020, largely fluctuating in the 30%–50% range. During this period, cryptocurrency, crude oil and financial markets were affected by real economic shock events, climate change actions, etc., and the overall market showed ups and downs. In August 2021, the surge in cryptocurrency prices prompted global regulators to intensify regulatory pressure on the cryptocurrency market; however, cross-continent regulatory collaboration was limited. In the same month, the COVID-19 Delta variant broke out in emerging markets with low vaccination rates, disrupting production and supply chains. In October 2021, US crude oil and natural gas prices surged, with crude oil closing above $80 per barrel for the first time. A climate change agreement was signed at the United Nations Climate Summit (COP26) on November 13, 2021. More than 190 countries worldwide have agreed to strengthen their carbon emissions reduction targets, making progress in global climate governance. However, there was a small increase in the index in November 2021, from approximately 40% on November 23, 2021 to approximately 60% on November 26, 2021. The surge in total volatility spillovers corresponded to the global panic over the designation of Omicron, a new variant of the coronavirus, as a global "variant of concern" by the WHO on November 26, 2021. Yields in the stock, oil, and bond markets plunged and cryptocurrency markets were trending lower as investors sought shelter from shocks.

Dynamic directional spillover indices have been used to study the temporal characteristics of directional spillover between various markets, as shown in Fig. 12A and B. Among these, Fig. 12A represents the dynamic spillover effects of each market FROM others, and Fig. 12B represents the dynamic spillover effects of each market TO others. Generally, markets with lower exposure to risk spillovers were more dominant in the risk transmission process and had higher risk spillovers to other markets. After the COVID-19 pandemic outbreak in 2020, the level of risk spillover exposure of various markets, such as the crude oil market, increased dramatically from February 2020, and the shock of extreme events led to an expansionary trend in the overall risk exposure of various markets. After March 2020, the global pandemic was brought under control to some extent, and the level of risk spillover in each market diminished. Concerns about health and global health policies may further evolve into concerns about health and environmental climate policies, with climate governance-related biodiversity and low pollution playing key roles in infectious pandemics.

Figure 13 presents the dynamics of directional net connectedness (NET) across markets with variability in the risk transmission active–passive scenario across markets. For the cryptocurrency market, the net spillover index of the upside and downside risks fluctuated alternately (positively and negatively) throughout the interval, reflecting the time-varying characteristics of risk spillovers in both directions in the cryptocurrency market. The fluctuations in upside risk and downside risk were more consistent, maintaining a relatively small spread. However, in the interval from February 2018 to May 2018, the cryptocurrency downside risk was more sensitive to fluctuations in other markets, and the net total directional connectedness was negative. In

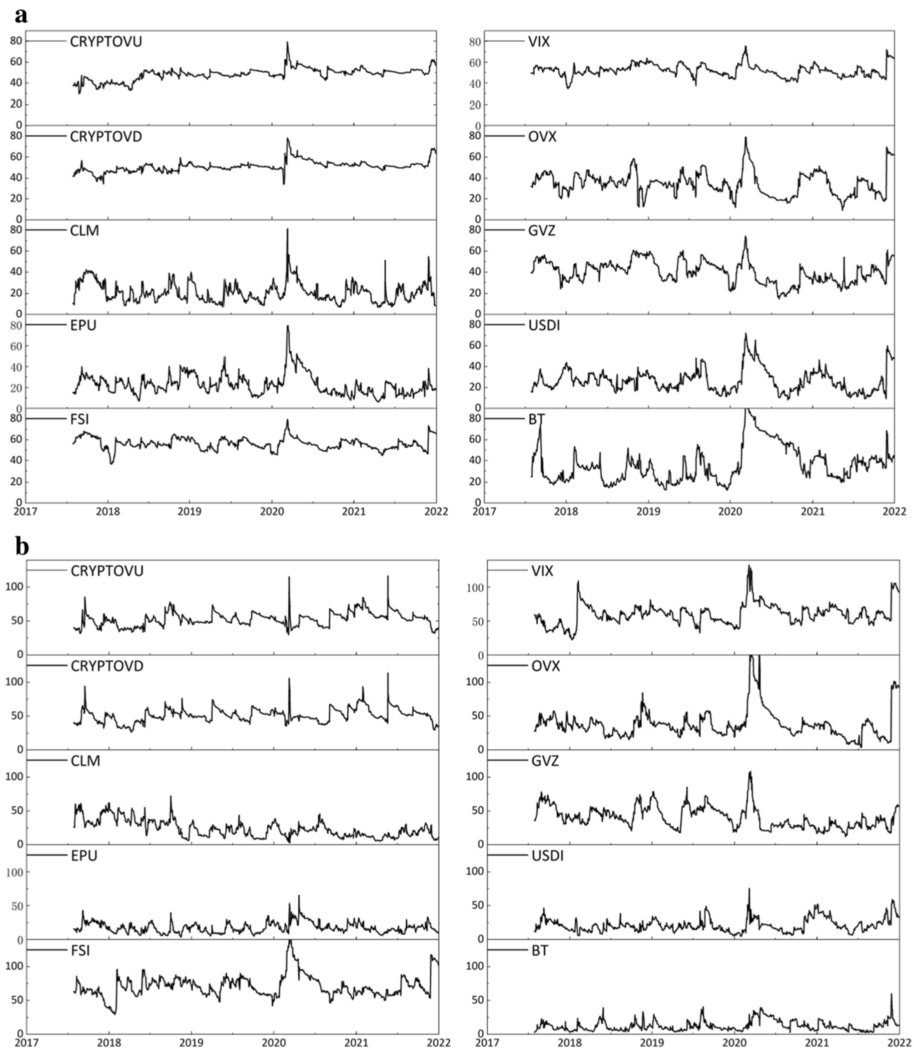

Fig. 12 A Dynamics of total directional connectedness "FROM" other markets B Dynamics of total directional connectedness "TO" other markets

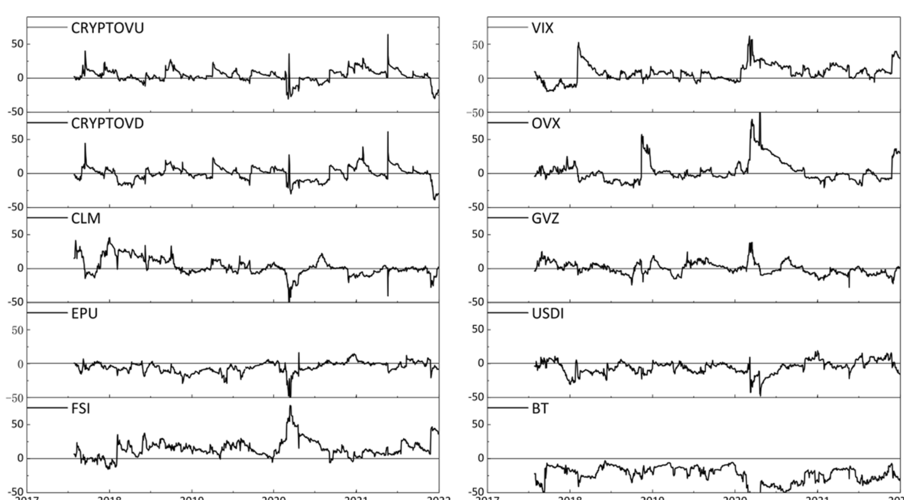

Fig. 13 Dynamics of directional net connectedness (NET) across markets

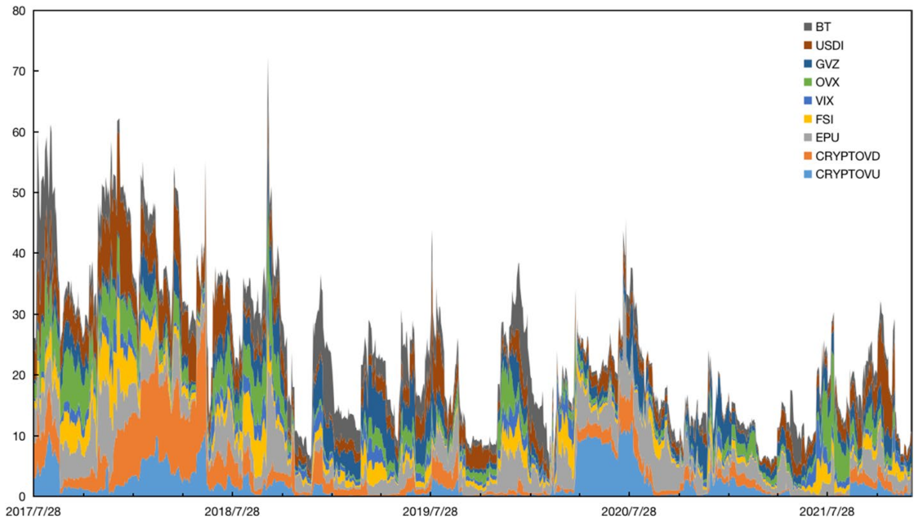

Fig. 14 Climate Risks Dynamic Directional Connectedness TO Others

addition, the cryptocurrency market downside risk was largely positive in the interval from August 2020 to August 2021, with a net risk spillover.

For climate risk, the level of net risk spillover from climate risk was largely above the axis until 2020, while in the interval from February 2020 to June 2020, climate risk was subject to greater risk spillover from other markets than from other markets. The impact of global extreme events led to dramatic effects on markets such as equities, crude oil, and bonds, with increased overall intermarket volatility and a negative level of net spillover from climate risk.

Throughout the sample period, the net spillover indices of the financial, international capital, and crude oil markets were predominantly positive, indicating that the spillover effects of these three markets on other markets were greater than those brought by other markets, with the three markets mainly acting as transmitters of risk spillover. In contrast, policy factors, exchange rate markets, and bond markets showed a net risk spillover effect during the overall sample period, all in a passive position of risk transmission. Finally, the gold market showed alternating positive and negative fluctuations, but the interval in the net spillover level accounted for more than 50% of the full sample interval, and the average level mainly showed the market characteristics of the risk-dominant factor.

3. Directional Spillover of volatility spillover between markets

Figure 14 illustrates climate risk spillovers to other markets from July 28, 2017, to December 30, 2022. The risk spillover from climate risk to other markets had time-varying characteristics. Climate change could lead to more frequent extreme events, such as floods, high temperatures and storms, which often have a large impact on a region in a short period of time. Coupled with slow environmental changes, such as sea level rise in the long term, climate change would have a significant impact on global economic life in the short and long terms, especially in countries and regions

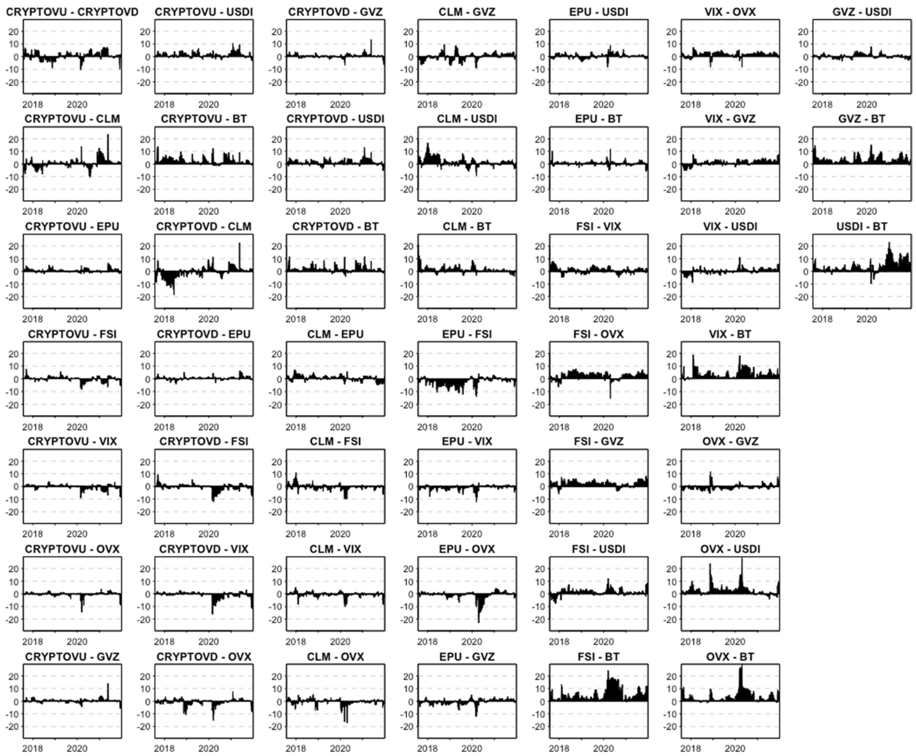

Fig. 15 Dynamic net pairwise directional connectedness (NPDC) Note: At the bilateral level, the net pairwise directional connectedness measure (NPDC) captured the comparison of the magnitude of impact between the two markets. For the market i–market j plot, when the NPDC is above the horizontal axis, market i has a stronger influence on market j, and the former has a higher level of risk spillover than the latter

with high vulnerability to climate change. Climate risk would impact on all sectors and economies, which would be further transmitted to various markets and even global financial markets. The high level of risk spillover from climate risk to exchange rate markets, bond markets, crude oil markets and policy uncertainty can be seen in Fig. 13. Climate-related financial risks could spill over further into the cryptocurrency market across sectors, so there is the potential for extreme weather to impact the infrastructure of cryptocurrencies. The spillover of climate risk to cryptocurrency market extremes was at a high level across the range, as shown in Fig. 14, but the risk spillover to cryptocurrency market upside risk was slightly different from downside risk. The spillover from climate risk to the downside risk of the cryptocurrency market was more significant before 2020, reaching a peak risk spillover of 20.33 on June 8, 2018. The uncertainty impact of climate risk on the financial system poses the risk of asset price declines in the short term. Between 2020 and 2021, the cryptocurrency market upside risk is subject to more risk spillover from climate risk, with a maximum value of 13.00 occurring on July 10, 2020.

Figure 15 represents the NPDC between different markets, showing risk spillovers at a bilateral level. For the two markets that include the cryptocurrency market, the cryptocurrency market exhibited more of a risk-receiving position compared with the uncertainties of the financial, international capital and crude oil markets. Consistent

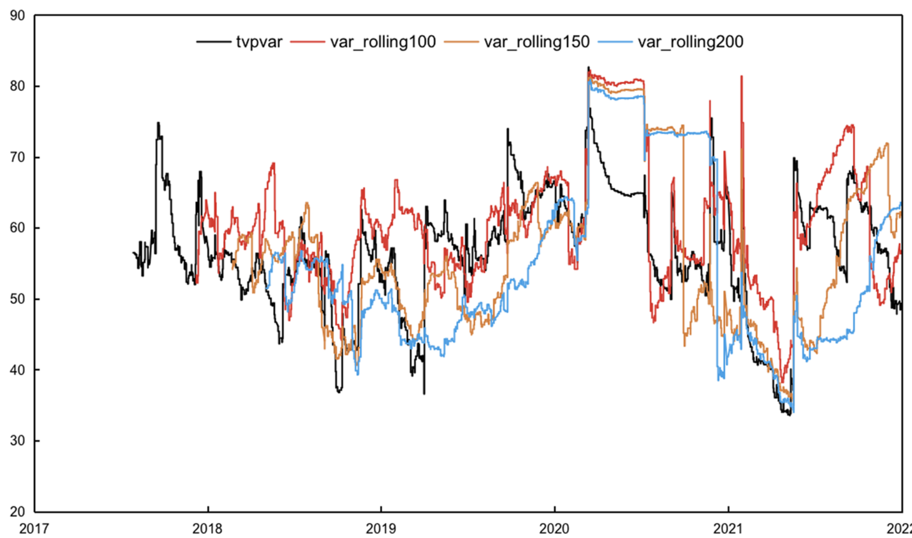

Fig. 16 Dynamic total connectedness index of cryptocurrency upside risk network based on a TVP-VAR model and three VAR models. Note: The black line corresponds to the total connectedness index of the upward cryptocurrency risk network established based on the TVP-VAR model in Fig. 5. The other three lines represent the total connectedness index of the upward risk network of cryptocurrencies established using the traditional sliding-window VAR model with window widths of 50, 150, and 200, respectively

with the analysis above, the prices of cryptocurrencies were more prone to surge and plunge with the price volatility of these markets in terms of oscillatory changes. Relative to the exchange rate, gold market and bond market, the cryptocurrency market exhibited more as a transmitter of volatility spillovers. It is worth noting that spillovers between cryptocurrency markets, financial markets and international capital markets rose significantly between 2020 and 2021 compared with 2017 and 2019, indicating the growing linkages and spillover effects between cryptocurrency markets and equity markets. The cryptocurrency market was no longer seen as a marginal market in the overall system, and the rise in risk transmission with other markets posed a greater uncertainty factor for the stability of the overall market. The dynamic results of the pairwise directional connectedness in Fig. 15 shows that there was a difference in the directional connectedness of climate risk to the upside and downside of extreme risk in the cryptocurrency market. Specifically, climate shocks had a slightly larger impact on downside risk than upside risk. Corresponding to the total connectedness table, the risk spillover of climatic factors to the upside of the cryptocurrency market was 2.1%, and that of the cryptocurrency market was 2.83%. The risk spillover results for the climate risk and cryptocurrency markets corresponded to each other at the overall interval-wide level and at the dynamic change level. In addition to dynamic risk spillovers to cryptocurrency market downside risk, climate risk also played a major role as a risk transmitter to policy uncertainty, bond markets, and exchange rate markets in our sample interval. This has been reflected by the weak information processing capacity of these markets themselves and their vulnerability to external risk contagion, showing the vulnerability of the stability of these markets to climate risks such as extreme weather events and the uncertainty of low-carbon transition.

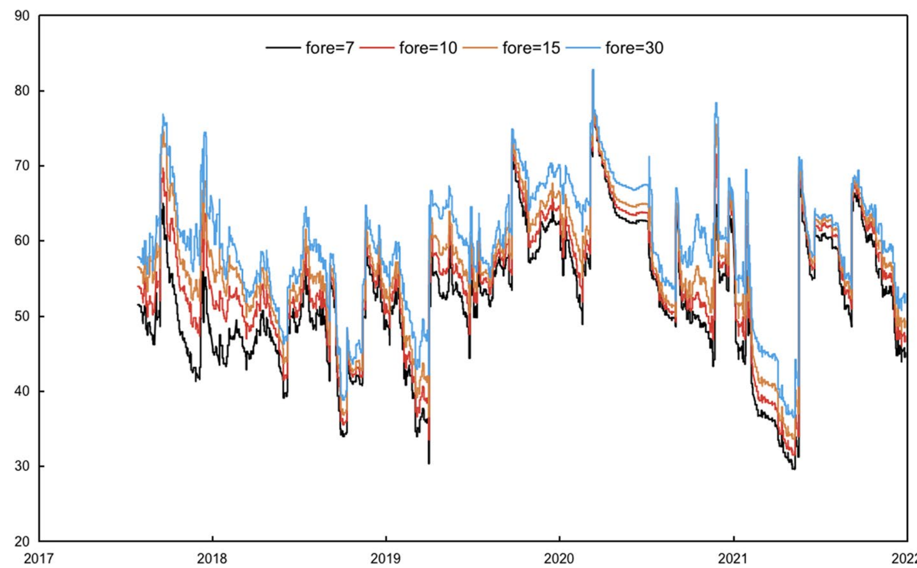

Fig. 17 Dynamic total connectedness index of cryptocurrency upside risk network based on a TVP-VAR model and three VAR models. Note: The black line corresponds to the total connectedness index of the upward risk network of cryptocurrencies established based on the TVP-VAR model with a forward forecasting horizon of seven days, as shown in Fig. 5. The other three lines represent the total connectedness index of the upward risk network of cryptocurrencies established using the TVP-VAR model with forward forecasting horizons of 10, 15, and 30 days

Robustness tests

TVP-VAR and VAR connectedness networks

Referring to Antonakakis et al. (2020), we first construct a connectedness network for the upward risk of cryptocurrencies using the traditional sliding-window VAR model, following the methodology of Diebold and Yilmaz (2012). Three different window sizes are chosen, namely 100, 150, and 200 days, to establish the models and compare their results with those of the TVP-VAR model. A comparison between the VAR model results with the sliding window and the TVP-VAR model results is shown in Fig. 16. As shown in Fig. 16, the TCI of the networks constructed using the four different models exhibited a certain level of consistency in terms of overall trends and magnitudes. Moreover, in 2020, the VAR model with a sliding window displayed a lower frequency of variations and larger fluctuations in the TCI than the TVP-VAR model. This can be attributed to the substantial impact of extreme events on the cryptocurrency market in 2020, which may have reduced the effectiveness of the sliding-window VAR model. In the other periods within the sample, the results of the four models were consistent.

TVP-VAR and VAR connectedness networks using different forecast steps

Next, we construct an upward risk network for cryptocurrencies based on the TVP-VAR-DY model. We introduce a modification by adjusting the forward forecasting horizon and selecting H-steps = 10, 15, and 30, representing forecasting periods of 15, 30, and 60 days, respectively, to establish a connectedness network. A comparison between the obtained dynamic results and the original TVP-VAR model, which results in a forecasting horizon of seven days, is shown in Fig. 17. The dynamic changes in the TCI for different forecasting horizons exhibit consistency, with minimal differences observed among the indices. This demonstrates the robustness of the model.

Conclusion

In this study, we first measured the extreme risks (upside risks and downside risks) of six different cryptocurrencies using the VaR method. Subsequently, extreme spillover networks for cryptocurrency markets upside and downside risks were constructed employing the TVP-VAR-DY method, with the overall extreme risk of the cryptocurrency markets measured by the connectedness indexes in the networks. Then, the second TVP-VAR-DY spillover network was built to examine the risk spillover of cryptocurrency markets' extreme risks and other uncertainties. By considering climate risk as a new uncertainty, along with uncertainties in economic policy and financial markets, some key findings were uncovered. First, the six cryptocurrencies examined exhibited interconnectedness, with more than 50% of extreme risk stemming from volatility spillovers across markets. Specifically, Bitcoin, Binance Coin, XRP and Dogecoin markets displayed a prominent external spillover effect, assuming a dominant role as transmitters within the cryptocurrency system. Second, in the second spillover network, the overall financial market uncertainty and uncertainties of international capital, crude oil, and gold markets acted as risk transmitters, while policy uncertainty and uncertainties of exchange rates and bond markets acted as risk receivers. Notably, climate shocks emerged as an overall risk transmitter, displaying a greater risk spillover to downside than upside risks. Moreover, the spillover effect of the cryptocurrency market from other markets increased significantly during 2020–2021 compared with 2017–2019. Extreme global events (e.g., COVID-19) exerted a significant impact on the risk spillover network within the cryptocurrency market and between the cryptocurrency market and uncertainties of other markets.

Based on the research findings, several policy implications can be drawn, highlighting the importance of proactive risk management, comprehensive regulatory frameworks, climate risk assessment and crisis preparedness to uphold the stability and resilience of the cryptocurrency market. First, market participants should implement robust risk-diversification strategies in response to the increasing risk linkages and diminished asset diversification in cryptocurrencies. This involves diversifying investments across varied asset classes and geographical regions to reduce reliance on a single cryptocurrency. Furthermore, given the observed interconnectedness and risk spillovers observed in the cryptocurrency market, it is crucial for governments and regulatory bodies to establish comprehensive regulatory frameworks. These frameworks should consider the links and potential risks associated with cryptocurrencies and include effective oversight and risk mitigation measures. International regulatory coordination is recommended to address the cross-border nature of cryptocurrencies and minimize the risk transmission from the cryptocurrency market to the broader financial system. Moreover, our research emphasizes the role of climate risk as a significant transmitter of overall risk in the cryptocurrency market, particularly concerning downside risks. Policymakers should closely monitor climate-related events and their impacts on cryptocurrency prices. Integrating climate risk assessment and monitoring mechanisms into regulatory frameworks can provide valuable insights for risk management and ensure the resilience of the cryptocurrency market. Additionally, policymakers should develop contingency plans and stress-testing mechanisms to evaluate the market's resilience during extreme global events, such as the COVID-19 pandemic, which includes assessing the effectiveness of risk management tools and ensuring sufficient liquidity to mitigate potential systemic risks.

The present paper acknowledges several limitations that can be addressed in future research. Although the TVP-VAR model exhibits the capability to capture the time-varying characteristics of vectors, in contrast to the traditional VAR model, it is not exempt from its own inherent limitations. The TVP-VAR model assumes that parameter changes occur in every period, which often leads to an underestimation of the error covariance matrix in the estimated state equation and, consequently, a closer proximity among the various state values. Regarding risk measurement, this study employed a widely used VaR method. Future research could explore alternative risk measurement methods, such as the expected shortfall (ES) method, marginal and systemic expected shortfall (MES), parametric generalized Pareto distribution (GPD), the skewed generalized error distribution (SGED), and nonparametric estimation. Additionally, future studies could consider utilizing higher-frequency intraday data to investigate the intraday risk spillover and connectedness between the cryptocurrency market and various sources of uncertainty. This approach would provide valuable insights into the dynamics of risk transmission and connectedness in the cryptocurrency market throughout the trading period.

Abbreviations

FROM	The directional total connectedness from others
NET	The net directional total connectedness
NPDC	The net pairwise directional connectedness
TCI	Total connectedness index
TO	The directional total connectedness to others
TVP-VAR	Time-varying parameters Vector-autoregressive model
VaR	Value-at-Risk

Acknowledgements
The authors are grateful to Daojuan Wang, associate professor of Aalborg University (daw@business.aau.dk) for her helpful discussions and comments on this work.

Funding
The authors would like to thank the support of a financial grant from the National Natural Science Foundation of China No. 72348003, 72022020, 71974159, 71974181, the Fundamental Research Funds for the Central Universities and MOE Social Science Laboratory of Digital Economic Forecasts and Policy Simulation at UCAS.

Author contributions
KG: Conceptualization, Writing-Original Draft, Writing—Reviewing and Editing. YK: Writing—Original Draft, Software, Calculation. QJ: Supervision, Writing—Reviewing, Data analysis. DZ: Supervision, Writing—Reviewing and Editing

Availability of data and materials
The authors confirm that datasets used and analyzed during the current study will be made available on reasonable request.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Received: 17 January 2023 Accepted: 6 December 2023
Published online: 12 September 2024

References

Aalborg HA, Molnár P, de Vries JE (2019) What can explain the price, volatility and trading volume of Bitcoin? Financ Res Lett 29:255–265. https://doi.org/10.1016/j.frl.2018.08.010

Addoum JM, Ng DT, Ortiz-Bobea A (2020) Temperature shocks and establishment sales. Rev Financ Stud 33:1331–1366. https://doi.org/10.1093/rfs/hhz126

Aharon DY, Umar Z, Vo XV (2021) Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies. Financ Innov 7:59. https://doi.org/10.1186/s40854-021-00274-w

Akhtaruzzaman M, Boubaker S, Nguyen DK, Rahman MR (2022) Systemic risk-sharing framework of cryptocurrencies in the COVID–19 crisis. Financ Res Lett. https://doi.org/10.1016/j.frl.2022.102787

Akyildirim E, Corbet S, Lucey B et al (2020) The relationship between implied volatility and cryptocurrency returns. Financ Res Lett 33:101212. https://doi.org/10.1016/j.frl.2019.06.010

Al Guindy M (2021) Cryptocurrency price volatility and investor attention. Int Rev Econ Financ 76:556–570. https://doi.org/10.1016/j.iref.2021.06.007

Andrada-Félix J, Fernandez-Perez A, Sosvilla-Rivero S (2020) Distant or close cousins: Connectedness between cryptocurrencies and traditional currencies volatilities. J Int Financ Mark Inst Money 67:101219. https://doi.org/10.1016/j.intfin.2020.101219

Antonakakis N, Chatziantoniou I, Gabauer D (2020) Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J Risk Financ Manag 13:84. https://doi.org/10.3390/jrfm13040084

Aysan AF, Demir E, Gozgor G, Lau CKM (2019) Effects of the geopolitical risks on Bitcoin returns and volatility. Res Int Bus Finance 47:511–518. https://doi.org/10.1016/j.ribaf.2018.09.011

Berkhout F, van den Hurk B, Bessembinder J et al (2014) Framing climate uncertainty: socio-economic and climate scenarios in vulnerability and adaptation assessments. Reg Environ Change 14:879–893

Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. J Econom 31:307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bonaparte Y (2023) Introducing the cryptocurrency vix: Cvix. Financ Res Lett 54:103712. https://doi.org/10.1016/j.frl.2023.103712

Bouri E, Molnár P, Azzi G et al (2017) On the hedge and safe haven properties of Bitcoin: is it really more than a diversifier? Financ Res Lett 20:192–198. https://doi.org/10.1016/j.frl.2016.09.025

Bouri E, Lau CKM, Lucey B, Roubaud D (2019) Trading volume and the predictability of return and volatility in the cryptocurrency market. Financ Res Lett 29:340–346. https://doi.org/10.1016/j.frl.2018.08.015

Bouri E, Gabauer D, Gupta R, Tiwari AK (2021a) Volatility connectedness of major cryptocurrencies: the role of investor happiness. J Behav Exp Financ 30:100463. https://doi.org/10.1016/j.jbef.2021.100463

Bouri E, Gupta R, Vo XV (2021b) Jumps in geopolitical risk and the cryptocurrency market : the singularity of Bitcoin

Brière M, Oosterlinck K, Szafarz A (2015) Virtual currency, tangible return: portfolio diversification with bitcoin. J Asset Manag 16:365–373. https://doi.org/10.1057/jam.2015.5

Caferra R, Vidal-Tomás D (2021) Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic. Finance Res Lett 43:101954. https://doi.org/10.1016/j.frl.2021.101954

Canh NP, Wongchoti U, Thanh SD, Thong NT (2019) Systematic risk in cryptocurrency market: evidence From DCC-MGARCH model. Financ Res Lett 29:90–100. https://doi.org/10.1016/j.frl.2019.03.011

Chowdhury MSR, Damianov DS, Elsayed AH (2022) Bubbles and crashes in cryptocurrencies: Interdependence, contagion, or asset rotation? Financ Res Lett 46:102494. https://doi.org/10.1016/j.frl.2021.102494

Conlon T, McGee R (2020) Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. Financ Res Lett 35:101607. https://doi.org/10.1016/j.frl.2020.101607

Corbet S, Lucey B, Yarovaya L (2021) Bitcoin-energy markets interrelationships - New evidence. Resour Policy 70:101916. https://doi.org/10.1016/j.resourpol.2020.101916

Da Z, Engelberg J, GAO P, (2011) In search of attention. J Financ N Y 66:1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x

das Neves RH, (2020) Bitcoin pricing: impact of attractiveness variables. Financ Innov 6:21. https://doi.org/10.1186/s40854-020-00176-3

De Vries A (2023) Cryptocurrencies on the road to sustainability: Ethereum paving the way for Bitcoin. Patterns. https://doi.org/10.1016/j.patter.2022.100633

Diebold FX, Yilmaz K (2009) Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ J Lond 119:158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold FX, Yilmaz K (2012) Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast 28:57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold FX, Yılmaz K (2014) On the network topology of variance decompositions: Measuring the connectedness of financial firms. J Econ 182:119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Dyhrberg AH (2016) Hedging capabilities of bitcoin. Is it the virtual gold? Financ Res Lett 16:139–144. https://doi.org/10.1016/j.frl.2015.10.025

Elsayed AH, Gozgor G, Yarovaya L (2022) Volatility and return connectedness of cryptocurrency, gold, and uncertainty: evidence from the cryptocurrency uncertainty indices. Finance Res Lett 47:102732. https://doi.org/10.1016/j.frl.2022.102732

Fang T, Su Z, Yin L (2020) Economic fundamentals or investor perceptions? the role of uncertainty in predicting long-term cryptocurrency volatility. Int Rev Financ Anal 71:101566. https://doi.org/10.1016/j.irfa.2020.101566

Fernandes MC, Dias JC, Nunes JPV (2021) Modeling energy prices under energy transition: A novel stochastic-copula approach. Econ Model 105:105671. https://doi.org/10.1016/j.econmod.2021.105671

Fernando R, Liu W, McKibbin WJ (2021) Global economic impacts of climate shocks, climate policy and changes in climate risk assessment. Clim Policy Chang Clim Risk Assess May 2021 CEPR Discuss Pap No DP16154

Fry J (2018) Booms, busts and heavy-tails: The story of Bitcoin and cryptocurrency markets? Econ Lett 171:225–229. https://doi.org/10.1016/j.econlet.2018.08.008

Ghosh SK, Hossain MdN, Khatun H (2022) The hedging role of US and Chinese stock markets against economic and trade policy uncertainty: lessons from recent turbulences. China Financ Rev Int. https://doi.org/10.1108/CFRI-08-2022-0154
Gil-Alana LA, Abakah EJA, Rojo MFR (2020) Cryptocurrencies and stock market indices? Are They Related, Res Int Bus Finance 51:101063. https://doi.org/10.1016/j.ribaf.2019.101063
Giupponi C, Borsuk ME, de Vries BJM, Hasselmann K (2013) Innovative approaches to integrated global change modelling. Environ Model Softw Environ Data News 44:1–9. https://doi.org/10.1016/j.envsoft.2013.01.013
Hartono P, Robiyanto R (2021) Can cryptocurrency, gold and bonds play a role as a safe haven for the Indonesian capital market? J Ekon Kuantitatif Terap. https://doi.org/10.24843/JEKT.2021.v14.i01.p01
Hasselmann K (1997) Climate-Change Research after Kyoto. Nat Lond 390:225–226. https://doi.org/10.1038/36719
Hong H, Li FW, Xu J (2019) Climate risks and market efficiency. J Econom 208:265–281. https://doi.org/10.1016/j.jeconom.2018.09.015
Hsu S-H, Sheu C, Yoon J (2021) Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions. North Am J Econ Financ 57:101443. https://doi.org/10.1016/j.najef.2021.101443
Ji Q, Bouri E, Gupta R, Roubaud D (2018) Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. Q Rev Econ Finance 70:203–213. https://doi.org/10.1016/j.qref.2018.05.016
Ji Q, Bouri E, Lau CKM, Roubaud D (2019a) Dynamic connectedness and integration in cryptocurrency markets. Int Rev Financ Anal 63:257–272. https://doi.org/10.1016/j.irfa.2018.12.002
Ji Q, Bouri E, Roubaud D, Kristoufek L (2019b) Information interdependence among energy, cryptocurrency and major commodity markets. Energy Econ 81:1042–1055. https://doi.org/10.1016/j.eneco.2019.06.005
Jiang S, Li Y, Lu Q et al (2021a) Policy assessments for the carbon emission flows and sustainability of Bitcoin blockchain operation in China. Nat Commun 12:1938–1938. https://doi.org/10.1038/s41467-021-22256-3
Jiang Y, Lie J, Wang J, Mu J (2021b) Revisiting the roles of cryptocurrencies in stock markets: a quantile coherency perspective. Econ Model 95:21–34. https://doi.org/10.1016/j.econmod.2020.12.002
Karim S, Naeem MA, Mirza N, Paule-Vianez J (2022) Quantifying the hedge and safe-haven properties of bond markets for cryptocurrency indices. J Risk Financ 23:191–205. https://doi.org/10.1108/JRF-09-2021-0158
Khalfaoui R, Mefteh-Wali S, Viviani J-L et al (2022) How do climate risk and clean energy spillovers, and uncertainty affect US stock markets? Technol Forecast Soc Change 185:122083. https://doi.org/10.1016/j.techfore.2022.122083
Klein T, Thu HP, Walther T (2018) Bitcoin is not the New Gold–A comparison of volatility, correlation, and portfolio performance. Int Rev Financ Anal 59:105–116. https://doi.org/10.1016/j.irfa.2018.07.010
Koop G, Korobilis D (2013) Large Time-Varying Parameter VARs. J Econ 177(2):185–198
Koop G, Pesaran MH, Potter SM (1996) Impulse response analysis in nonlinear multivariate models. J Econ 74:119–147. https://doi.org/10.1016/0304-4076(95)01753-4
Koutmos D (2018) Return and volatility spillovers among cryptocurrencies. Econ Lett 173:122–127. https://doi.org/10.1016/j.econlet.2018.10.004
Kwon JH (2021) On the factors of Bitcoin's value at risk. Financ Innov 7:87. https://doi.org/10.1186/s40854-021-00297-3
Kyriazis NA (2020) The effects of geopolitical uncertainty on cryptocurrencies and other financial assets. SN Bus Econ 1:5. https://doi.org/10.1007/s43546-020-00007-8
Li S, Huang Y (2020) Do Cryptocurrencies Increase the Systemic Risk of the Global Financial Market?
Lucey BM, Vigne SA, Yarovaya L, Wang Y (2022) The cryptocurrency uncertainty index. Financ Res Lett 45:102147. https://doi.org/10.1016/j.frl.2021.102147
Martinez-Diaz L, Keenan JM (2020) Managing climate risk in the US financial system. US Commodity Futures Trading Commission
Milunovich G (2022) Assessing the connectedness between Proof of Work and Proof of Stake/Other digital coins. Econ Lett 211:110243. https://doi.org/10.1016/j.econlet.2021.110243
Mora C, Rollins RL, Taladay K et al (2018) Bitcoin emissions alone could push global warming above 2°C. Nat Clim Change 8:931–933. https://doi.org/10.1038/s41558-018-0321-8
Naeem MA, Lucey BM, Karim S, Ghafoor A (2022) Do financial volatilities mitigate the risk of cryptocurrency indexes? Financ Res Lett 50:103206. https://doi.org/10.1016/j.frl.2022.103206
OECD (2017) Green finance and investment mobilising bond markets for a low-carbon transition. OECD Publishing, Paris
Okorie DI, Lin B (2020) Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy. Energy Econ 87:104703. https://doi.org/10.1016/j.eneco.2020.104703
Ozturk SS (2020) Dynamic connectedness between bitcoin, gold, and crude oil volatilities and returns. J Risk Financ Manag 13:275. https://doi.org/10.3390/jrfm13110275
Peng Y, Albuquerque PHM, Camboim de Sá JM et al (2018) The best of two worlds: forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression. Expert Syst Appl 97:177–192. https://doi.org/10.1016/j.eswa.2017.12.004
Pesaran HH, Shin Y (1998) Generalized impulse response analysis in linear multivariate models. Econ Lett 58:17–29. https://doi.org/10.1016/S0165-1765(97)00214-0
Pham L, Karim S, Naeem MA, Long C (2022) A tale of two tails among carbon prices, green and non-green cryptocurrencies. Int Rev Financ Anal 82:102139. https://doi.org/10.1016/j.irfa.2022.102139
Ren B, Lucey B (2022) Do clean and dirty cryptocurrency markets herd differently? Finance Res Lett 47:102795. https://doi.org/10.1016/j.frl.2022.102795
Schelling TC (2009) International coordination to address the climate challenge. Innov Camb Mass 4:13–21. https://doi.org/10.1162/itgg.2009.4.4.13
Schinckus C, Nguyen CP, Ling FCH (2020) Crypto-currencies trading and energy consumption. Int J Energy Econ Policy 10:355–364. https://doi.org/10.32479/ijeep.9258
Soylu PK, Okur M, Catikkas O, Altintig ZA (2020) Long memory in the volatility of selected cryptocurrencies: Bitcoin, ethereum and ripple. J Risk Financ Manag 13:107. https://doi.org/10.3390/jrfm13060107
Stoll C, Klaaßen L, Gallersdörfer U (2019) The carbon footprint of bitcoin. Joule 3:1647–1661. https://doi.org/10.1016/j.joule.2019.05.012

Su C-W, Qin M, Tao R et al (2020) Can Bitcoin hedge the risks of geopolitical events? Technol Forecast Soc Change 159:120182. https://doi.org/10.1016/j.techfore.2020.120182
Truby J, Brown RD, Dahdal A, Ibrahim I (2022) Blockchain, climate damage, and death: Policy interventions to reduce the carbon emissions, mortality, and net-zero implications of non-fungible tokens and Bitcoin. Energy Res Soc Sci 88:102499. https://doi.org/10.1016/j.erss.2022.102499
Vranken H (2017) Sustainability of bitcoin and blockchains. Curr Opin Environ Sustain 28:1–9. https://doi.org/10.1016/j.cosust.2017.04.011
Wang Y, Lucey BM, Vigne SA, Yarovaya L (2022) The effects of central bank digital currencies news on financial markets. Technol Forecast Soc Change 180:121715. https://doi.org/10.1016/j.techfore.2022.121715
Wang Y, Wei Y, Lucey BM, Su Y (2023) Return spillover analysis across central bank digital currency attention and cryptocurrency markets. Res Int Bus Financ 64:101896. https://doi.org/10.1016/j.ribaf.2023.101896
Wendl M, Doan MH, Sassen R (2023) The environmental impact of cryptocurrencies using proof of work and proof of stake consensus algorithms: a systematic review. J Environ Manage 326:116530. https://doi.org/10.1016/j.jenvman.2022.116530
Yen K-C, Cheng H-P (2021) Economic policy uncertainty and cryptocurrency volatility. Finance Res Lett 38:101428. https://doi.org/10.1016/j.frl.2020.101428
Zhang X, Lu F, Tao R, Wang S (2021) The time-varying causal relationship between the Bitcoin market and internet attention. Financ Innov Heidelb 7:1–19. https://doi.org/10.1186/s40854-021-00275-9

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.