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Research article

Bitcoin and crypto-mining stocks: A quantile connectedness approach

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Abstract: In this paper, we studied the extreme connectedness between Bitcoin and crypto-mining stocks using the quantile connectedness approach of Ando et al. (2022). We estimated the connectedness (i.e., the direction and strength of spillover effects) at the median, extreme lower, and extreme upper quantiles. Our results revealed a highly interconnected system, with Bitcoin identified as a net transmitter of shocks. RIOT and MARA also emerged as major net transmitters in the system, while GREE and NILE were net receivers. The spillover effects were more pronounced during extreme market conditions compared to normal conditions. Moreover, the connectedness of the system progressively increased, peaking in 2021 when China banned crypto-mining. The extreme and dynamic connectedness identified in this study offers valuable insights for investors regarding hedging strategies and portfolio allocation, as well as for regulators focused on financial stability and systemic risk.

Keywords: Bitcoin; crypto-mining; stock market; quantile connectedness; spillover

JEL Code: C58, F36, G11, G15

1. Introduction

The cryptocurrency market has faced significant challenges over the past several years, including declining prices and fraudulent activities. While these setbacks have led some analysts to question the long-term viability of cryptocurrencies, the market retains a substantial market capitalization of US$1.05 trillion, with around 320 million global users. These figures demonstrate the continued relevance of cryptocurrencies in the financial landscape, albeit with inherent risks and challenges that must be effectively managed. China's ban on proof-of-work cryptocurrency mining in spring 2021 forced many miners to close their Chinese operations and seek new locations in North America, with Texas in particular emerging as a prime destination. Consequently, the United States has become the primary hub for proof-of-work data centers, with many Bitcoin miners listed as public companies. Here, we explore the extreme connectedness[1] between Bitcoin and crypto-mining stocks, particularly focusing on the direction and strength of the spillover effects under both normal and extreme market conditions.

Easley et al. (2019) developed a game theoretic model to explain the relationship between cryptocurrency miners, users, and the role of transaction fees in crypto markets. Their theory underscores the importance of factors such as Bitcoin price and mining-based revenues (block rewards). Building on this, we empirically explore the relationship between Bitcoin prices and crypto-mining stock prices. Similar studies on the relationship between commodity prices and the stocks of commodity-producing companies include Dar et al. (2019) for gold and gold mining stocks and Maghyereh and Abdoh (2021) for oil and oil-producing stocks. Borri (2019) calculated the conditional tail-risk in the cryptocurrency markets, noting that while exposure to this risk is significant within the market, it is less so compared to other global assets like stocks or gold. Recent years have also seen increased research interest in the spillover effects between industry-specific equities and the corresponding tokens. The return-and-volatility spillover between renewable energy tokens and fossil fuel markets, travel and tourist tokens and tourism equities, meme tokens and meme stocks, Tether and cryptocurrencies, and electric utility index and crypto-mining stocks have been studied (Griffin and Shams, 2020; Yousaf et al., 2022, Halaburda and Yermack, 2023; and Yousaf et al., 2023). The literature shows that the interconnectivity and spillover effects are characterized by asymmetry and heterogeneity in the tails, suggesting that they not only differ in direction and strength across quantiles but also fluctuate over time. In particular, the strength of spillovers tends to rise at times of economic disturbance, such as the COVID-19 pandemic.

In this study, we have three primary objectives: To estimate the time-varying return connectedness between Bitcoin and crypto-mining stocks; to investigate the asymmetry of return spillovers under extreme market conditions; and to explore the implications of these dynamics for portfolio diversification and risk management.

This paper contributes to the literature in three ways. First, it sheds light on the extreme connectedness between Bitcoin and crypto mining stocks. For example, in January 2023, Bitcoin's 2.2% rise to $22,956 triggered a surge in the prices of 18 Bitcoin mining stocks, of 19 stocks tracked by The Block, including significant gains for Bitfarms, Marathon Digital Holdings, and Hive Blockchain Technologies. However, the 2021 bull market led to increased borrowing by Bitcoin miners, negatively impacting their financial standing during the subsequent bear market (The Block, 2023). While anecdotal evidence suggests a strong correlation between Bitcoin and crypto-mining

[1] Connectedness is a statistical measure of the level of spillover effects among financial assets or markets (Diebold and Yilmaz, 2014), whereas the term "extreme" alludes to the upper and lower quantiles that allow us to study the connectedness in both the bullish and bearish market phases.

stocks, a more rigorous analysis of their dynamic relationships under varying market conditions is warranted. Our work provides insights for investors to make informed investment decisions and manage risk effectively, and for policymakers to understand the nature of these financial networks to inform their policy responses to systemic crises.

Second, it adds to the literature on the impact of commodity prices on the stocks of companies that produce the underlying commodities. Baur and Trench (2022) documented a "flight-to-quality" phenomenon, where investors flee to gold from gold mining stocks during extreme shocks, but flee only from non-gold mining stocks during less extreme shocks. Gold mining stocks and gold are more coherent than other stocks and gold (Paul et al., 2019). Similarly, Dar et al. (2019) suggest that gold mining stocks can serve as proxies for gold prices, though the correlation is positive but imperfect. Maghyereh and Abdoh (2021) explored the relationship between oil price shocks and oil and gas stock returns, finding that the relationship is more pronounced during normal times and is more driven by oil demand shocks than by supply shocks. We aim to investigate the extreme connectedness between Bitcoin and crypto-mining stocks, providing insights into potential risks and opportunities in these emerging asset classes.

Finally, we introduce the quantile-connectedness approach of Ando et al. (2022) to this area of research. Cryptocurrencies and related equities are characterized by extreme price movements, fat tails, and nonlinear dependencies (Ahmed et al., 2024; Kyriazis et al., 2024; Härdle et al., 2016; Padhan & Kocoglu, 2025). This method enables us to comprehensively study the tail risk that spreads throughout the cryptocurrency and stock markets, revealing the intricate structure inside this disputed and volatile industry. Following Ando et al. (2022), we apply a quantile-based measure of connectedness using a quantile VAR model, similar to Diebold and Yilmaz (2012), based on the quantile regression methodology of Koenker and Bassett (1978). For this approach, we use quantile regression to construct VAR models at the extreme high and low quantiles that help us discover and quantify the dynamics of connectedness during exceptionally large positive and negative shocks. For robustness, we also apply the mean-based connectivity technique based on Diebold and Yilmaz (2012) and find qualitatively similar results.

Our results suggest that the system is highly interconnected: A shock in one variable is likely to spill over to other variables in the network system. We find that RIOT and MARA exhibit the highest connectedness within the system, indicating that these assets are more influential within the system. Bitcoin acts as a net transmitter of shocks in the system, and its spillover effect was more pronounced before China's 2021 crypto-mining crackdown. In general, we find stronger spillover effects during extreme market periods compared to normal periods. The dynamic connectedness analysis shows that the connectedness of the system increased sharply in 2021 when China banned cryptocurrency mining, peaking at 70% before declining towards the end of 2022. The total connectedness of the system at the extreme lower quantile and extreme upper quantile has been consistently high, with greater time-series fluctuations in the latter. The dynamics of the connectedness found in our research have significant implications for investors and regulators regarding financial stability and systemic risk.

The remainder of this paper is organized as follows: In Section 2, we review the relevant literature. In Section 3, we describe the empirical model. In Section 4, we discuss the data and provide summary statistics. In Section 5, we present the empirical results. In Section 6, we conclude the paper.

2. Literature review

We build on the growing literature on asset interconnectedness, contagion, and systemic risk, particularly in the context of emerging digital asset classes. While other researchers focus on average connectedness, we argue that market participants are more concerned with extreme events, tail risk transmission, and asymmetric responses. The quantile connectedness framework of Ando et al. (2022) is well-suited to uncover these dynamics. Theoretically, our study relates to the literature on financial contagion (Forbes and Rigobon, 2002), tail dependence (Tobias and Brunnermeier, 2016), and hedge asset properties (Baur and Lucey, 2010) by showing that Bitcoin and crypto mining stocks do not behave independently under stress, challenging assumptions about their diversification benefits.

Recent global health, social, and financial crises have intensified the connectedness between financial markets. Our study engages with two distinct strands of literature. The first entails the relationship between stock markets and cryptocurrency markets, while the second includes the connections between the values of commodity-producing firms and underlying commodities. By analyzing the dynamics in the connections between Bitcoin and crypto-mining stocks, this paper contributes to both bodies of research. We discuss each stream in more detail below.

2.1. Cryptocurrency and stock markets

Several researchers have investigated the potential of cryptocurrencies as investment tools for risk diversification amid adverse market shocks. The premise is that cryptocurrency markets are influenced by different forces than stock markets: while stock prices generally reflect economic conditions and firm fundamentals, cryptocurrency prices are driven more by media attention and investor sentiment.Researchers such as Feng et al. (2018), Bouri et al. (2017), Dyhrberg (2016), Borri (2019), Kliber et al. (2019), Gil-Alana et al. (2020), Mariana et al. (2021), and Bouri et al. (2018) provide mixed findings on the relationship between cryptocurrencies and stock markets. Some researchers find a negative correlation, suggesting that cryptocurrencies may serve as a safe-haven asset, such as Bitcoin, in the case of extreme down movements in Asian stocks (Bouri et al., 2017), or as a diversifier or hedge, depending on the economic and regulatory contexts of different countries (Kliber et al., 2019).

However, other researchers have found that cryptocurrencies are not completely isolated from other assets and that their returns are closely and positively related to those of other asset classes, particularly commodities (Bouri et al., 2018). Studies such as those by Conlon and McGee (2020) and Klein et al. (2018) show that Bitcoin does not function as a safe haven during crises and may increase portfolio downside risk when held alongside traditional assets like the S&P 500. Additionally, Bitcoin is more volatile, less liquid, and more costly to trade than conventional safe-haven assets such as gold (Smales, 2019). Thus, until the cryptocurrency market matures, its viability as a hedge or diversification tool remains in question.

Moreover, Yousaf and Yarovaya (2022) examined linkages between Islamic cryptocurrencies and stock markets, noting that Onegram, a gold-backed cryptocurrency, effectively mitigated portfolio risk during the COVID-19 pandemic. Yousaf et al. (2023) investigated the connectedness between energy cryptocurrencies and conventional asset classes, identifying energy cryptocurrencies as effective diversifiers. However, their correlations can shift abruptly during market shocks, such as during COVID-19 and the Russia-Ukraine conflict. While information flows between crypto and stock markets (Yousaf et al., 2023), the direction, strength, and mechanisms of the spillover effects remain largely unexplored.

In conclusion, the relationship between cryptocurrency and stock markets has been explored only recently, with inconclusive evidence; some studies report a weak or negative correlation, while others show a positive connection. This gap in the literature calls for more focused and rigorous research.

2.2. Gold and gold mining stocks

With a long history of numerous empirical investigations on the relationship between products or services and the firm value of their providers, in this section, we mainly focus on the literature encompassing the relationships between gold prices and gold mining stocks as an example.

Early works such as McDonald and Solnick (1977) and Tufano (1998) revealed that gold-stock prices are positively linked to gold prices and that the elasticity of gold stock returns to gold prices is often higher than one. Recent research, however, provides more nuanced insights by including more rigorous methods and more specific settings. For example, Reboredo and Ugolini (2017) studied the quantile causality between gold prices and gold mining stocks and found significant variations across nations and regions. In contrast, Batten et al. (2017) reported no evidence of an asymmetric relationship between gold prices and gold stocks across quantiles. Dar et al. (2019) found a positive correlation between gold and gold mining stocks at some time horizons but noted that this relationship can be less significant or absent at other times.

Paul et al. (2019) found moderate coherence between gold and gold mining stocks in the U.S. and U.K., while Troster et al. (2019) used Granger-causality quantile regression to identify unidirectional causality from stock market volatility to volatilities in gold, gold mining, and silver markets, supporting the flight-to-safety hypothesis. Troster et al. (2019) also found unidirectional spillover from volatilities of stock, gold, and silver to the gold mining stocks in lower- and upper-tail quantiles and conclude that gold mining stocks are good substitutes for gold. Baur et al. (2021) further suggest that during severe financial shocks, investors prefer gold bullion over equities, including those of gold mining companies. For less severe shocks, investors tend to flee from all equities except gold mining stocks. Shahzad et al. (2021) studied the time-variation and heterogeneity in the causality-in-quantile and found that gold returns depend positively on gold mining stock returns in the low and high quantiles, while gold returns predict the gold stock returns negatively in the median quantile. The results support a time-varying short-term embedded real option in gold for gold stocks.

Shaikh (2021) examined investor sentiment overreactions in the COVID-19 pandemic in commodities (e.g., gold, silver, crude oil, and energy) and gold mining stocks. COVID-19 has induced economic uncertainty that has impacted all commodities, most significantly in history, except the safe-haven asset of gold. Baur and Trench (2022) further observed a COVID-induced decoupling of gold companies from gold prices, indicating that gold companies are exposed to market risk and are not a safe haven. They also discovered that investors treat gold explorers, developers, and producers differently, in terms of their relationship with the gold price, in normal times, but more equally during COVID-19.

In summary, the relationship between gold and gold mining stocks remains a topic of ongoing research and debate.[2] Early studies suggest a strong positive correlation between gold prices and gold stocks, while more recent research indicates that this relationship can vary significantly in direction and strength across countries, regions, time horizons, and research settings. Furthermore, financial shocks and crises, such as the COVID-19 pandemic, can have a significant impact. In this paper, we study similar dynamics in the connectedness between cryptocurrencies and crypto-mining stocks during normal times and the COVID pandemic.

2.3. Relevance to green finance and sustainability transitions

Although we focus on the financial connectedness between Bitcoin and crypto-mining stocks, its broader relevance lies in its implications for green finance and sustainable investing. Crypto-mining operations, particularly those run by publicly traded firms like MARA and RIOT, are highly energy-intensive and often rely on fossil-fuel-based electricity grids. Moreover, these environmental concerns position the sector at the heart of the ongoing debates around climate change, carbon-intensive assets, and ESG-aligned capital flows.

Recent research underscores the link between cryptocurrency markets and environmental attention. For instance, Qing & Alnafrah (2025) found that environmental sentiment significantly affects crypto-asset pricing, as it acts as a potential catalyst for clean energy investment. Similarly, Alnafrah (2025) highlighted the efficiency of green innovations and renewables in mitigating sustainability risks. Our findings of strong connectedness and systemic vulnerability in mining stocks suggest that these assets may be particularly sensitive to future environmental regulations, such as mining bans, emissions taxation, or ESG-related capital reallocation (Alnafrah, 2024).

Further, Xie et al. (2025) proposed blockchain-based innovation systems to promote sustainability-oriented digital finance. This offers a pathway to reconcile technological innovation with green policy goals. Our study contributes to this discussion by offering early empirical evidence of how climate-related risks might transmit through crypto-linked financial assets. It is critical for financial stability and sustainable asset pricing.

This reinforces the importance of our research within the Green Finance agenda, providing investors and regulators with valuable insights on managing climate-related financial risk and promoting environmentally sustainable investment strategies.

3. Methodology

By applying the quantile-connectedness methodology of Ando et al. (2022), we can quantify the quantile-based spillover effects across Bitcoin and crypto-mining stocks. This approach is particularly well-suited for examining this relationship due to the highly volatile, non-normal, and regime-sensitive nature of these markets (Ahmed et al., 2024; Kyriazis et al., 2024). The quantile-based method enables the analysis of spillovers across the return distribution, contrary to focusing only on the average

[2] We also find such kinds of studies for oil (Diaz and de Gracia, 2017; Maghyereh and Abdoh, 2021) and gold and oil (Ntantamis and Zhou, 2015).

relationships. This is critical for capturing asymmetric dependencies, especially during tail events when systemic risk and contagion are most likely to arise (Härdle et al., 2016; Padhan & Kocoglu, 2025). Moreover, it enables the identification of directional risk transmission under different market conditions, providing valuable insights for investors, regulators, and firms operating within the crypto ecosystem (Chatziantoniou et al., 2021). The quantile connectedness approach of Ando et al. (2022) aligns closely with Markowitz's portfolio theory. It captures how dependence structures shift under extreme market conditions, precisely when diversification benefits matter most. Traditional mean-based connectedness measures assume symmetric relationships, which can underestimate co-movement during crises (Diebold & Yilmaz, 2009, 2014). In contrast, quantile-based connectedness highlights the asymmetric, tail-dependent relationships that can erode diversification during downturns. Thus, it offers more realistic inputs for portfolio risk management. Moreover, high lower-quantile connectedness can signal joint downside risk exposure across assets, conceptually overlapping with systemic beta and tail risk measures such as CoVaR (Tobias & Brunnermeier, 2016) and SRISK (Brownlees & Engle, 2017). While we do not estimate these systemic risk metrics directly, the presence of strong spillovers in the lower quantiles may serve as a proxy for systemic vulnerability. Overall, this study provides valuable insights into extreme risk transmission, helping regulators and institutional investors better manage systemic exposure to crypto-linked assets.

Following Ando et al. (2022) and Diebold and Yilmaz (2012), we define the infinite-order-based VMA (vector moving average) specifications as:

$$y_t = \mu(\tau) + \sum_j^p \Phi_j(\tau)\, y_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \Omega_i(\tau) u_{t-i} \tag{1}$$

Following the literature (e.g., Koop et al., 1996; Pesaran and Shin, 1998; Ando et al., 2022), we define the "generalized forecast error variance decomposition (GFEVD) with a forecast horizon of H" as:

$$\Theta_{ij}^{g}(H) = \frac{\Sigma(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Omega_h(\tau) \Sigma(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Omega_h(\tau) \Sigma(\tau) \Omega_h(\tau)' e_i\right)} \tag{2}$$

The symbol e_i stands for the zero-vector having unity at the ith location. The elements in the decomposition matrix are normalized as:

$$\widetilde{\Theta}_{ij}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1}^{k} \Theta_{ij}^{g}(H)}, \text{ with } \sum_{j=1}^{k} \widetilde{\Theta}_{ij}^{g}.1 \text{ and } \sum_{i,j=1}^{k} \widetilde{\Theta}_{ij}^{g}(H) = 1 \tag{3}$$

To quantify features of spillovers (TO, FROM, NET, and TCI), we follow Ando et al. (2022) and Diebold and Yilmaz (2012) and define the GFEVD-based spillover measurements as:

$$TO_{j,t} = \sum_{i=1,,i\neq j}^{k} \widetilde{\Theta}_{ij,t}^{g}(H) \tag{4}$$

$$FROM_{j,t} = \sum_{i=1,,i\neq j}^{k} \widetilde{\Theta}_{ji,t}^{g}(H) \tag{5}$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \tag{6}$$

$$TCI_t = \frac{\sum_{i,j=1,,i\neq j}^{k} \tilde{\Theta}_{ij}^{g}(H)}{k-1} \tag{7}$$

As in Diebold and Yilmaz (2012), "the influence of variable j on variable i is shown by $TO_{j,t}$. The effect of i on j is represented by $FROM_{j,t}$. The negative (positive) value of $NET_{j,t}$ denotes the net recipient (transmitter) of spillover. TCI_t stands for the average degree of overall connectivity."

To better inform investors in their portfolio management, we also compute the optimal portfolio weights (Kroner and Ng, 1998), hedge ratios (Kroner and Sultan, 1993), and hedging effectiveness (Ku et al., 2007), in addition to the quantile connectedness analysis, utilizing the conditional volatilities and covariance from the estimations of the DCC-GARCH model.

The optimal portfolio weights are given as:

$$w_{BS,t} = \frac{h_{S,t} - h_{BS,t}}{h_{B,t} - 2h_{BS,t} + h_{\acute{S},t}} \tag{8}$$

$$w_{BS,t} = \begin{cases} 0, & If\ w_{BS,t} < 0 \\ w_{BS,\acute{t}}, & If \leq\ 0 \leq 1 \\ 1, & If\ w_{BS,t} > 1 \end{cases}$$

where $w_{BS,t}$ represents the weight of Bitcoin at time *t* in a portfolio of Bitcoin and crypto-mining stock worth one dollar. $h_{S,t}$, $h_{BS,t}$, and $h_{B,t}$ represent the conditional variance of crypto-mining stock, the conditional covariance between crypto-mining stock and Bitcoin, and the conditional variance of Bitcoin, respectively. Additionally, the weight of crypto-mining stock in a dollar-sized portfolio of Bitcoin and crypto-mining stock is $1 - w_{BS,t}$.

The optimal hedging ratio is:

$$\beta_{BS,t} = \frac{h_{BS,t}}{h_{\acute{S},t}} \tag{9}$$

where $\beta_{BS,t}$ is the optimal hedge ratio, and $h_{BS,t}$ and $h_{S,t}$ are the conditional covariance between crypto-mining stock and Bitcoin and the conditional variance of crypto-mining stock, respectively. The conditional variances and covariances are based on the DCC-GARCH model estimated above.

The hedging effectiveness is given by:

$$HE = \frac{Variance_{Unhedged} - Variance_{hedged}}{Variance_{Unhedged}} \tag{10}$$

where HE represents the hedging effectiveness, $Variance_{Unhedged}$ indicates the variance of returns of the Bitcoin-only portfolio, and $Variance_{hedged}$ is the variance of the portfolio returns of Bitcoin and crypto-mining stock.

4. Data

For this study, we use daily data for Bitcoin and ten highly capitalized, representative crypto-mining stocks: RIOT - Riot Platform Inc., MARA - Marathon Digital Holdings Inc., HIVE - HIVE Blockchain Technologies Ltd., HUT - Hut 8 Mining Corp, CLSK - CleanSpark Inc., WULF - TeraWulf Inc., BTBT - Bit Digital Inc., GREE - Greenidge Generation Holdings Inc., NILE - BitNile Holdings Inc., and BTCM

- BIT Mining Limited. We select these stocks based on their largest capitalization and influence on the market (Yousaf et al., 2024; Halaburda and Yermack, 2023). The sample period covers March 21, 2018 to January 13, 2023. The Bitcoin data are collected from coinmarketcap.com, while the data on the crypto-mining stocks are gathered from investing.com. This selection of highly capitalized stocks in the crypto-mining sector ensures a comprehensive network analysis of the interconnectedness between Bitcoin and crypto-mining stocks.

Figure 1 provides a visual representation of the prices of Bitcoin and crypto-mining stocks, while Figure 2 displays the daily returns of these assets. These figures enable us to observe trends and patterns in the prices and returns of Bitcoin and the selected stocks. There appear to be significant co-movements in the figures, though with varying speeds and strengths.

Based on the summary statistics in Table 1, it is apparent that the assets exhibit varying levels of mean returns and total risk. In particular, Bitcoin and MARA stand out with the highest mean returns, whereas NILE and BTCM have the lowest. In terms of standard deviations, the most volatile assets in the sample are NILE and CLSK, while Bitcoin is the least volatile, suggesting that Bitcoin alone is a relatively safer investment compared to the crypto-mining stocks under consideration.

Additionally, the excess kurtosis present in most assets, particularly GREE and CLSK, implies a higher probability of extreme events for these assets. Positive skewness, except for Bitcoin, WULF, and BTCM, indicates that the returns of most assets are generally skewed to the right, implying a higher probability of positive daily returns. The results from the Jarque-Bera test reveal that none of the return series follow a normal distribution, suggesting that investors cannot rely on the assumption of normality in their investment decisions. The augmented Dickey-Fuller (ADF) test confirms that all return series are stationary, indicating no long-term trend in the returns.

Overall, the summary statistics suggest that investing solely in highly capitalized crypto-mining stocks is a high-risk strategy, whereas Bitcoin alone appears to be a comparatively safer and more profitable asset. Additionally, investors must account for the non-normal distribution of returns while making investment decisions.

Table 2 presents the correlation coefficients between the returns of Bitcoin and the ten crypto-mining stocks. The positive correlation coefficients suggest that Bitcoin and cryptocurrency mining equities generally move in the same direction. Among the stock pairs, RIOT and MARA have the highest correlation coefficient of 0.762, indicating a strong positive correlation between the two assets. In contrast, the pair of WULF and NILE has the weakest relationship, with the lowest correlation coefficient of 0.115. These results suggest that while Bitcoin and the selected crypto-mining stocks tend to move together, the strength of the pairwise correlations varies substantially.

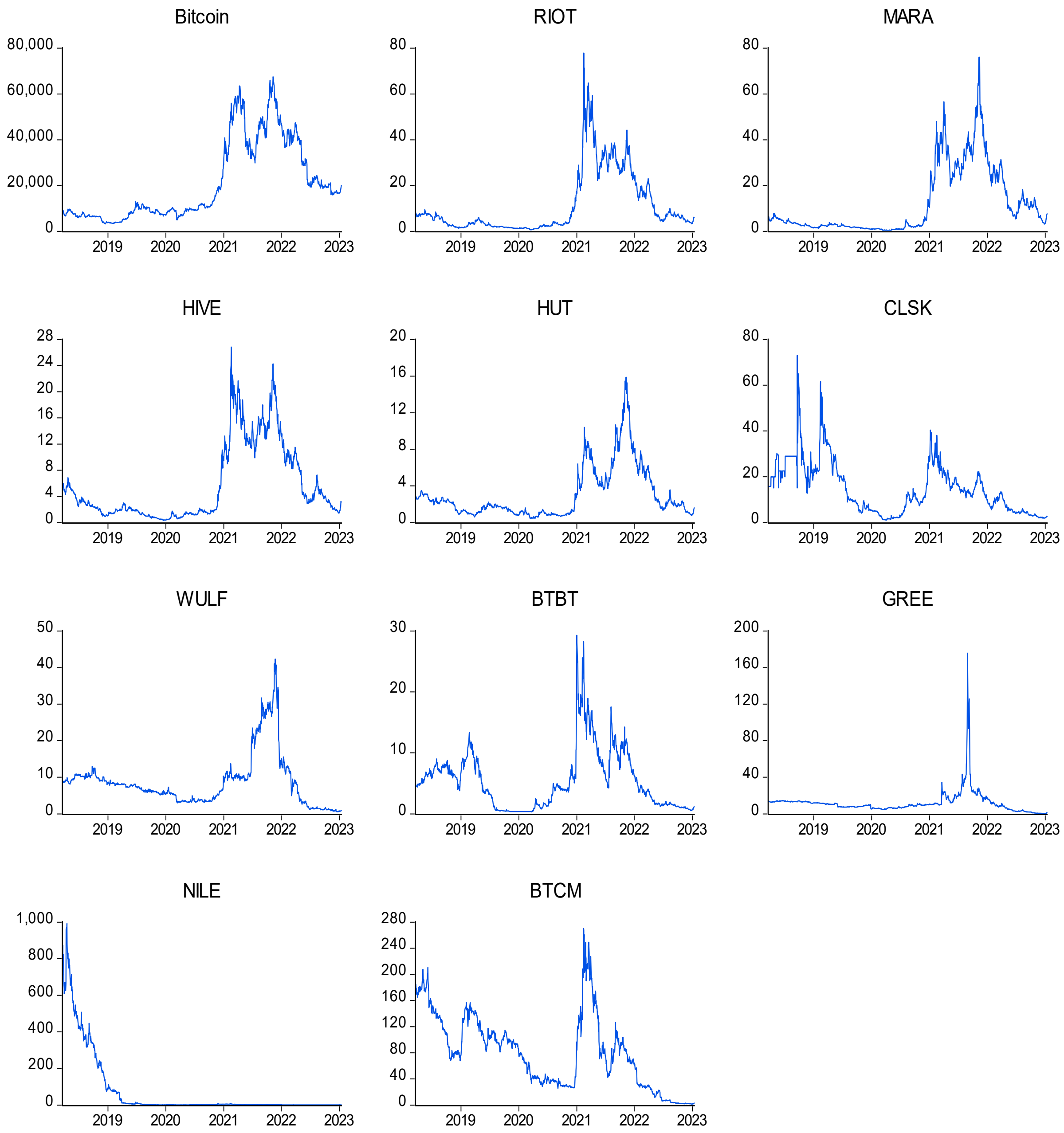


Figure 1. Prices of Bitcoin and crypto-mining stocks.

Table 1. Summary statistics.

	Mean	Max	Min	S. Dev.	Skew	Kurt	J-B	ADF
BITCOIN	0.0007	0.203	−0.465	0.045	−1.063	14.709	7164.0 [a]	−35.893 [a]
RIOT	−0.0002	0.395	−0.352	0.074	0.527	6.102	542.7 [a]	−35.919 [a]
MARA	0.0003	0.635	−0.315	0.084	1.039	8.018	1492.0 [a]	−35.260 [a]
HIVE	−0.0005	0.375	−0.288	0.075	0.453	5.154	276.3 [a]	−36.092 [a]
HUT	−0.0005	0.429	−0.274	0.073	0.648	6.052	556.2 [a]	−35.589 [a]
CLSK	−0.0015	1.582	−0.738	0.101	3.188	60.259	167899.2 [a]	−42.949 [a]
WULF	−0.0019	0.496	−0.513	0.066	−0.080	13.786	5886.5 [a]	−35.515 [a]
BTBT	−0.0011	0.740	−0.436	0.088	1.406	14.586	7189.7 [a]	−27.718 [a]
GREE	−0.0021	1.199	−0.571	0.074	3.285	70.106	229970.9 [a]	−33.596 [a]
NILE	−0.0072	1.217	−0.889	0.104	2.161	39.487	68286.9 [a]	−38.546 [a]
BTCM	−0.0034	0.353	−0.528	0.069	−0.496	13.506	5632.8 [a]	−34.522 [a]

Notes: Max-maximum, Min-minimum, S.Dev.-standard deviation, skew-skewness, kurt-kurtosis, J-B-Jarque Berra test, ADF-Augmented Dicky Fuller test. RIOT- Riot Platform Inc., MARA- Marathon Digital Holdings Inc., HIVE-HIVE Blockchain Technologies Ltd, HUT- Hut 8 Mining Corp, CLSK- CleanSpark Inc., WULF-TeraWulf Inc., BTBT- Bit Digital Inc., GREE- Greenidge Generation Holdings Inc., NILE- BitNile Holdings Inc., and BTCM- BIT Mining Limited. [a] refers to the level of significance at 1%.

Table 2. Unconditional correlations.

	BITCOIN	RIOT	MARA	HIVE	HUT	CLSK	WULF	BTBT	GREE	NILE	BTCM
BITCOIN	1.000										
RIOT	0.547 [a]	1.000									
MARA	0.519 [a]	0.762 [a]	1.000								
HIVE	0.568 [a]	0.612 [a]	0.610 [a]	1.000							
HUT	0.531 [a]	0.568 [a]	0.595 [a]	0.586 [a]	1.000						
CLSK	0.137 [a]	0.203 [a]	0.178 [a]	0.185 [a]	0.155 [a]	1.000					
WULF	0.160 [a]	0.180 [a]	0.187 [a]	0.173 [a]	0.165 [a]	0.115 [a]	1.000				
BTBT	0.247 [a]	0.352 [a]	0.323 [a]	0.269 [a]	0.295 [a]	0.156 [a]	0.145 [a]	1.000			
GREE	0.140 [a]	0.206 [a]	0.206 [a]	0.194 [a]	0.242 [a]	0.136 [a]	0.144 [a]	0.184 [a]	1.000		
NILE	0.234 [a]	0.306 [a]	0.341 [a]	0.239 [a]	0.208 [a]	0.100 [a]	0.115 [a]	0.190 [a]	0.119 [a]	1.000	
BTCM	0.269 [a]	0.288 [a]	0.262 [a]	0.246 [a]	0.278 [a]	0.159 [a]	0.195 [a]	0.262 [a]	0.171 [a]	0.120 [a]	1.000

Notes: RIOT- Riot Platform Inc, MARA- Marathon Digital Holdings Inc., HIVE-HIVE Blockchain Technologies Ltd., HUT- Hut 8 Mining Corp, CLSK- CleanSpark Inc., WULF-TeraWulf Inc., BTBT- Bit Digital Inc., GREE- Greenidge Generation Holdings Inc., NILE- BitNile Holdings Inc., and BTCM- BIT Mining Limited. [a] refers to the level of significance at 1%.

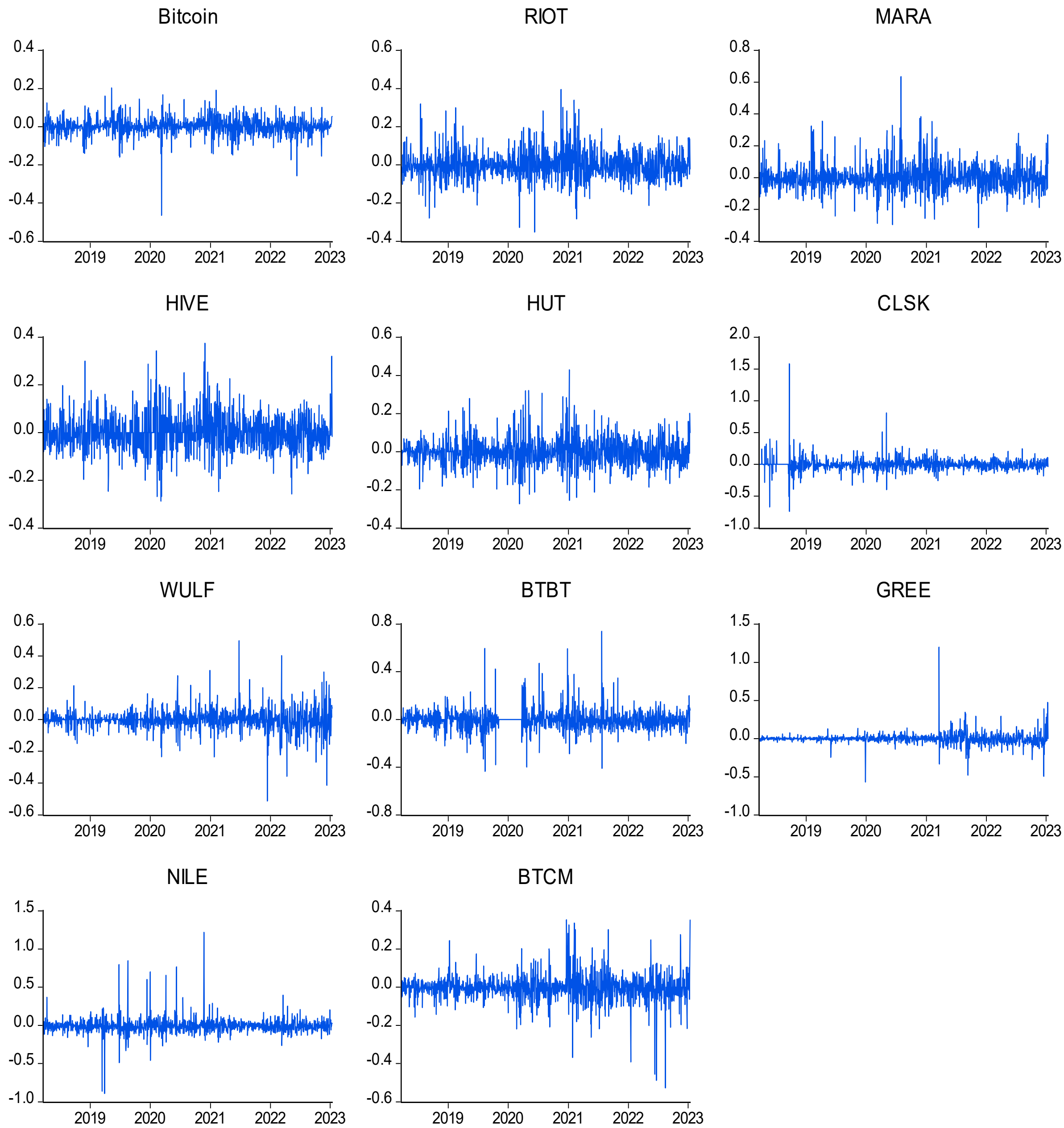


Figure 2. Daily returns of Bitcoin and crypto-mining stocks.

5. Quantile-connectedness analysis and results

5.1. Spillover effects estimation

To estimate the spillover effects for the sample period, we apply the quantile-connectedness methodology of Ando et al. (2022) using eleven variables, including Bitcoin and ten crypto-mining stocks. This approach performs a generalized variance decomposition at the median and various quantiles, enabling us to quantify the direction and strength of spillovers within the cryptocurrency and stock markets.

In contrast, WULF, GREE, and BTCM exhibit the lowest connectedness, with values of 10.40%, 16.42%, and 22.78%, respectively, indicating that these variables are less influential.

In terms of the influence of a variable on the system, the "TO" row shows that RIOT has the highest connectedness of 80.72%, followed by Bitcoin at 60.78%, indicating that these two are the most influential in the system. Yousaf et al. (2023) report similar findings by identifying Bitcoin as a key influencer in the system of energy cryptocurrencies and other assets. In contrast, WULF, GREE, and BTCM exhibit the lowest connectedness, with values of 10.40%, 16.42%, and 22.78%, respectively, indicating that these variables are less influential.

Additionally, the spillovers from the system to each variable (the "FROM" column) and the net directional connectedness are noteworthy. RIOT and Bitcoin receive the highest spillovers from the system, at 65.18% and 60.59%, respectively, while WULF, GREE, and BTCM receive the least, with 19.11%, 21.25%, and 33.00%.

The net directional connectedness reveals the overall influence of each variable on the system. A positive net directional connectedness value indicates that the variable is a net transmitter of shocks, whereas a negative value suggests that the variable is a net receiver of shocks. In this study, most variables are net receivers of shocks, as they have negative net connectedness values. However, RIOT, MARA, HIVE, HUT, and Bitcoin have positive values, implying that these variables are more likely to transmit shocks to others.

Overall, the total connectedness index (TCI) of the system is 44.66%, indicating that the system is highly interconnected, and idiosyncratic shocks are strongly propagated within the system. Thus, investors should carefully consider the connectedness, in direction and strength, of the system when making investment decisions to avoid potential losses due to spillover effects.

Table 3. Static connectedness at median (Q=0.50).

	RIOT	MARA	HIVE	HUT	CLSK	WULF	BTBT	GREE	NILE	BTCM	Bitcoin	FROM
RIOT	34.82	17.53	11.17	9.38	4.15	0.91	4.17	1.75	3.73	2.31	10.09	65.18
MARA	17.99	34.97	10.81	10.01	4.23	0.87	3.90	1.47	4.62	2.03	9.10	65.03
HIVE	12.53	11.77	39.27	10.74	3.68	0.80	3.09	1.55	2.88	2.16	11.54	60.73
HUT	10.86	10.77	10.79	41.84	3.46	0.80	3.92	2.25	2.08	2.49	10.75	58.16
CLSK	5.54	5.57	4.29	4.02	65.29	0.94	3.89	1.82	3.08	2.38	3.19	34.71
WULF	2.40	2.14	1.95	1.72	1.44	80.89	1.92	1.30	1.73	2.18	2.32	19.11
BTBT	6.04	5.18	3.95	4.84	3.86	0.99	63.85	1.79	2.60	2.82	4.07	36.15
GREE	2.49	2.25	2.14	3.60	2.64	1.12	2.47	78.75	1.53	1.27	1.73	21.25
NILE	6.44	7.48	4.62	3.46	3.81	1.25	3.17	1.44	62.63	2.23	3.47	37.37
BTCM	4.42	3.72	3.77	4.25	3.04	1.52	3.77	1.68	2.31	67.00	4.52	33.00
Bitcoin	12.01	10.37	12.38	11.00	3.09	1.20	3.86	1.38	2.38	2.91	39.41	60.59
TO	80.72	76.77	65.89	63.02	33.40	10.40	34.16	16.42	26.94	22.78	60.78	TCI
NET	15.54	11.74	5.15	4.85	−1.30	−8.70	−1.99	−4.83	−10.42	−10.22	0.19	44.66

Notes: RIOT- Riot Platform Inc., MARA- Marathon Digital Holdings Inc., HIVE-HIVE Blockchain Technologies Ltd., HUT- Hut 8 Mining Corp, CLSK- CleanSpark Inc., WULF-TeraWulf Inc., BTBT- Bit Digital Inc., GREE- Greenidge Generation Holdings Inc., NILE- BitNile Holdings Inc., and BTCM- BIT Mining Limited. NET=TO-FROM. TCI is the total connectedness index of the system.

5.2. Extreme market conditions

The results in Table 4 display the pairwise directional connectedness at the extreme lower quantile (i.e., Q=0.05). The "FROM" column presents the total directional connectedness from all others to each variable, and the "TO" row shows the total directional connectedness from each variable to others. The "NET" row reflects the net directional connectedness of each variable.

These findings reveal that, in extremely sluggish market conditions, the connectedness between assets and the system is significantly higher than during median market conditions. RIOT, MARA, and HIVE exhibit the highest connectedness to the system, with values of 95.76%, 94.28%, and 93.93%, respectively. Bitcoin also demonstrates a high level of connectedness, at 90.39%. The assets with low connectedness from the system are GREE, NILE, and CLSK, with connectedness values of 68%, 74.9%, and 80.77%, respectively.

In terms of net directional connectedness, RIOT shows the highest net positive directional connectedness, positioning it as the largest transmitter of shocks in the network, while GREE exhibits the highest net negative directional connectedness, making it the largest receiver of shocks. BTCM stands out with the smallest absolute value (i.e., closer to zero), indicating it is neither a significant receiver nor transmitter of spillovers. In contrast, Bitcoin's net directional connectedness of 5.07% further demonstrates its influential role in the system. The total connectedness of the system at this extreme lower quantile is 84.46%, suggesting that the overall system is highly interconnected at this level of market stress.

Table 5 presents the pairwise directional connectedness at the extreme upper quantile (Q=0.95). The results show that during booming market conditions, RIOT has the highest connectedness to the system at 98.27%, while GREE has the lowest at 68.8%. The connectedness from the system remains relatively high for all variables, with HUT exhibiting the highest connectedness of 87.13% and GREE the lowest at 83.14%.

In terms of net directional connectedness, RIOT displays the highest positive net connectedness of 11.69%, identifying it as a significant net transmitter of spillovers. In contrast, GREE shows the largest negative net connectedness at −14.34%, making it the biggest net receiver of spillovers. NILE has the smallest absolute value of net connectedness of 1.14%, indicating its minimal association with other assets.

The total connectedness of the system at the extreme upper quantile is 85.38%, which is higher than the total connectedness of 44.66% observed at the median, but comparable with the total connectedness at the extreme lower quantile (84.46%). This suggests that the spillover effects are more pronounced during extreme market conditions compared to normal market conditions.

Figure 3 complements Tables 3, 4, and 5 by visualizing the net pairwise spillover between Bitcoin and crypto-mining stocks at the median, extreme lower quantile, and extreme upper quantile. The connectedness varies significantly in terms of direction and strength across assets and under different market conditions.

Our findings of the asymmetric connectedness are consistent with other studies. For instance, Yousaf et al. (2022) analyzed the interconnectedness between renewable energy tokens and fossil fuel markets and discovered more asymmetry and heterogeneity in the tails of returns compared to the mean and median. Conversely, Feng et al. (2018) suggested that cryptocurrencies act as a diversifier for stock markets, akin to gold, due to their left-tail and cross-tail independence, though they do not offer the same tail hedging benefits as gold. Borri (2019) found that cryptocurrencies are subject to tail risk within crypto markets but not in other markets like U.S. equities or gold. These findings, including ours, have significant implications for investors seeking to diversify their portfolios with digital assets and mining stocks.

Table 4. Static connectedness at the extreme lower quantile (Q=0.05).

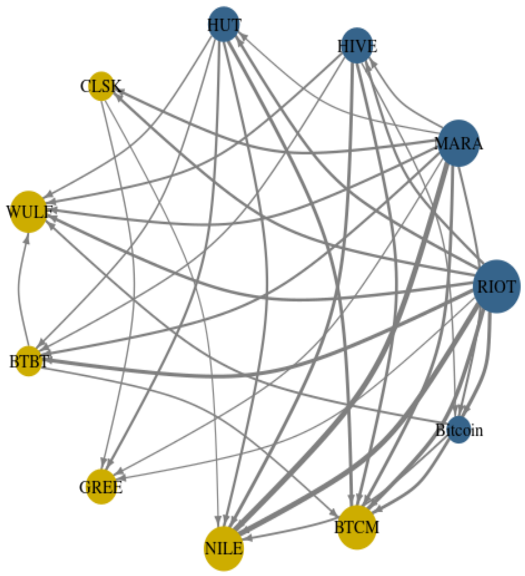
	RIOT	MARA	HIVE	HUT	CLSK	WULF	BTBT	GREE	NILE	BTCM	Bitcoin	FROM
RIOT	14.12	11.22	10.26	9.65	7.86	6.97	8.16	6.42	7.77	7.82	9.75	85.88
MARA	11.31	14.42	9.91	10.03	8.03	6.75	7.94	6.35	8.05	7.79	9.41	85.58
HIVE	10.32	10.02	14.4	10.18	7.92	7.34	7.70	6.42	7.43	8.27	10.01	85.60
HUT	9.98	10.21	10.12	14.12	7.73	7.14	8.50	7.06	7.30	8.16	9.68	85.88
CLSK	9.10	8.88	9.03	8.80	15.81	8.22	8.28	7.18	7.53	8.68	8.49	84.19
WULF	8.64	8.27	9.00	8.45	8.61	16.36	8.11	7.24	7.39	8.94	9.00	83.64
BTBT	9.46	9.08	8.67	9.11	8.47	7.78	15.98	6.92	7.58	8.47	8.48	84.02
GREE	8.56	8.28	8.52	8.70	8.00	7.91	8.12	18.16	7.26	8.15	8.35	81.84
NILE	9.21	9.68	9.02	8.47	8.11	7.61	7.90	6.64	16.84	7.94	8.58	83.16
BTCM	8.93	8.78	9.22	8.95	8.32	8.32	8.31	7.15	7.33	16.07	8.63	83.93
Bitcoin	10.26	9.87	10.2	9.90	7.74	7.64	7.87	6.64	7.25	7.97	14.68	85.32
TO	95.76	94.28	93.93	92.26	80.77	75.69	80.89	68.00	74.9	82.18	90.39	TCI
NET	9.89	8.70	8.33	6.37	−3.42	−7.96	−3.13	−13.84	−8.26	−1.75	5.07	84.46

Notes: RIOT- Riot Platform Inc., MARA- Marathon Digital Holdings Inc., HIVE-HIVE Blockchain Technologies Ltd., HUT-Hut 8 Mining Corp, CLSK- CleanSpark Inc., WULF-TeraWulf Inc., BTBT- Bit Digital Inc., GREE- Greenidge Generation Holdings Inc., NILE- BitNile Holdings Inc., and BTCM- BIT Mining Limited. NET=TO-FROM. TCI is the total connectedness index of the system.

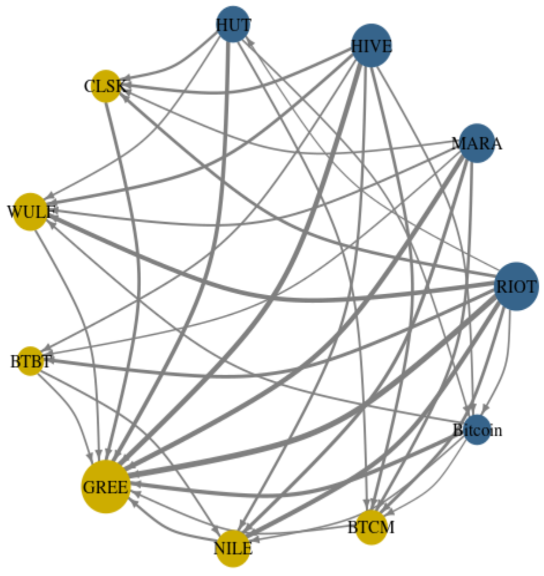
Table 5. Static connectedness at the extreme upper quantile (Q=0.95).

	RIOT	MARA	HIVE	HUT	CLSK	WULF	BTBT	GREE	NILE	BTCM	Bitcoin	FROM
RIOT	13.42	10.92	10.26	9.84	8.09	7.23	8.27	6.69	7.81	8.07	9.39	86.58
MARA	11.02	12.96	10.15	9.93	8.41	7.64	8.18	6.36	8.05	7.84	9.46	87.04
HIVE	10.68	9.69	13.53	9.59	8.19	7.92	8.35	6.59	7.98	7.90	9.58	86.47
HUT	10.43	9.81	10.04	12.87	8.06	7.78	8.41	7.21	7.98	8.19	9.22	87.13
CLSK	9.34	9.18	9.37	9.13	15.14	7.84	8.34	6.95	8.07	8.3	8.34	84.86
WULF	8.99	8.57	9.17	8.54	8.31	16.08	8.66	7.10	7.90	8.25	8.44	83.92
BTBT	9.63	8.88	9.18	8.82	7.96	8.16	15.24	7.42	7.81	8.51	8.39	84.76
GREE	8.96	8.33	8.65	8.88	8.28	7.99	8.22	16.86	7.76	7.90	8.17	83.14
NILE	9.66	9.48	9.10	8.50	8.18	7.76	8.66	6.75	15.92	7.72	8.27	84.08
BTCM	9.37	9.05	9.15	9.10	8.32	8.11	8.53	7.14	7.63	14.93	8.68	85.07
Bitcoin	10.18	9.74	10.42	9.98	8.02	7.61	8.00	6.59	7.54	8.06	13.87	86.13
TO	98.27	93.63	95.48	92.31	81.82	78.04	83.62	68.8	78.53	80.74	87.94	TCI
NET	11.69	6.59	9.01	5.18	−3.04	−5.87	−1.14	−14.34	−5.55	−4.34	1.81	85.38

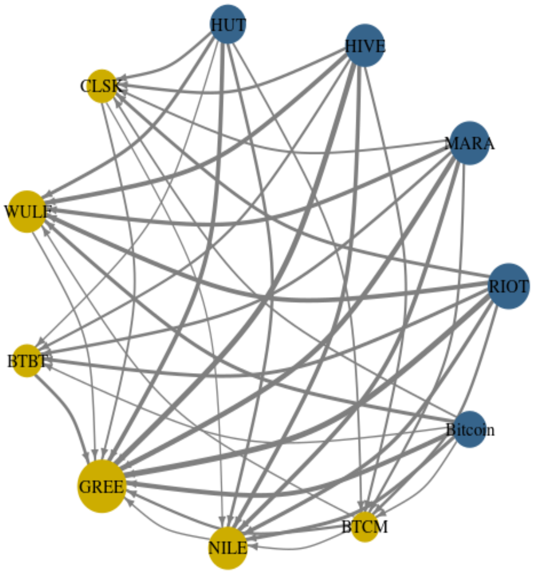
Notes: RIOT- Riot Platform Inc., MARA- Marathon Digital Holdings Inc., HIVE-HIVE Blockchain Technologies Ltd., HUT- Hut 8 Mining Corp, CLSK- CleanSpark Inc., WULF-TeraWulf Inc., BTBT- Bit Digital Inc., GREE- Greenidge Generation Holdings Inc., NILE- BitNile Holdings Inc., and BTCM- BIT Mining Limited. NET=TO-FROM. TCI is the total connectedness index of the system.



(a) Median (Q=0.50)



(b) Extreme lower quantile (Q=0.05)



(c) Extreme upper quantile (Q=0.95)

Figure 3. Net pairwise spillover: Directed and weighted network.

5.3. Time-varying connectedness and market dynamics

In this section, we examine the time-varying connectedness between Bitcoin and crypto mining stocks across quantiles, highlighting shifts in market dynamics. Figure 4 depicts the dynamic connectedness of the system over the sample period, with three graphs illustrating total connectedness of the system at the median value, extreme lower quantile, and extreme upper quantile.

The first graph for the median value shows an increasing trend in connectedness over time, with fluctuations and a significant increase to 35% in the first quarter of 2020 due to the COVID-19 pandemic. The connectedness continues to increase sharply, peaking at 70% in 2021. This is followed by a slight dip and a decline toward the end of 2022, likely related to turmoil in the crypto market, including the bankruptcy of FTX. Overall, the graph provides insight into the changing connectedness of the system over time, with implications for systemic risk management.

The second graph in Figure 3 indicates that total connectedness at the extreme lower quantile (Q=0.05) began at a high of 84%, dropping to 82% until the COVID-19 outbreak, which spiked connectedness to 86%. Afterward, the measure quickly falls back to the initial level. The connectedness of the system since then shows an overall increasing trend with small cycles of ups and downs. Toward the end of the sample period, the total connectedness of the system was recorded as 88%, the highest in our analysis.

The third graph for the extreme upper quantile reveals a different pattern, with consistently high connectedness, starting above 84% and experiencing fluctuations until mid-2019, followed by two notable spikes: One in mid-2019 and another just before 2020. Connectedness fell to 82% in 2020 but increased again, peaking at 88% before dropping back to 86%. The connectedness in this quantile appears to be more volatile. Along with the fluctuations, the connectedness in this quantile has an overall increasing trend. The high levels of connectedness in the extreme upper and lower quantiles have implications for investment strategies at times of uncertainty.

Overall, these results show that the connectedness between Bitcoin and crypto mining stocks has been increasing over time. Conlon and McGee (2020) also demonstrate that Bitcoin has a higher correlation with stock markets and tends to decrease in value alongside the S&P 500 during crises, suggesting that Bitcoin does not function as a safe-haven asset. Klein et al. (2018) argue that Bitcoin differs from gold in asset properties and connections to equity markets, and is more likely to go down with downward markets, implying it may not provide stable hedging capabilities. Thus, investors should exercise caution when considering Bitcoin as a diversification or a hedging instrument, highlighting the need for further attention and research in this area.

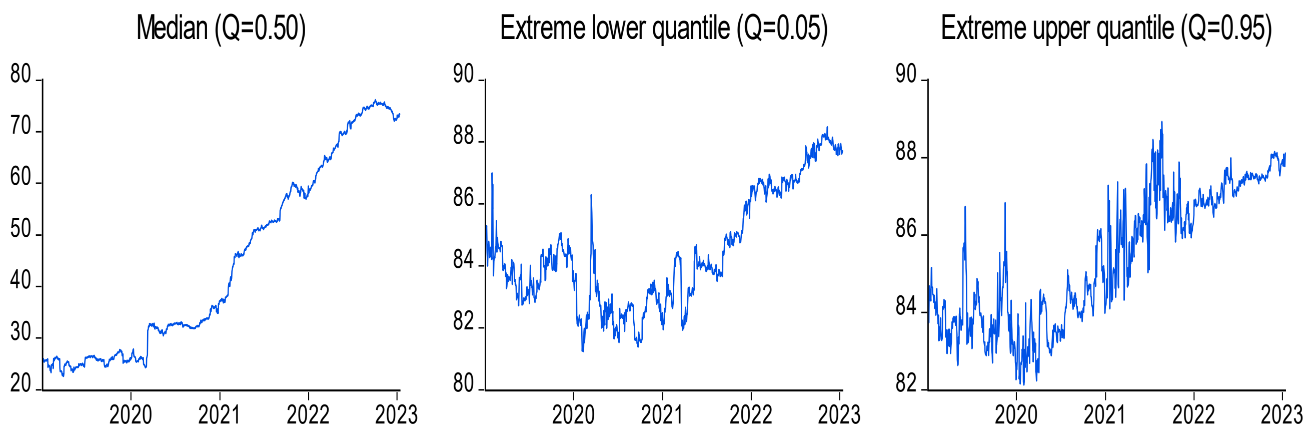


Figure 4. Total spillover index at the median, extreme lower quantile, and extreme upper quantile.

Figure 5 illustrates the difference in total connectedness between the extreme upper and lower quantiles, highlighting changes in market connectedness post-COVID-19. Before the pandemic, connectedness in the extreme lower quantile exceeded that in the upper quantile, resulting in predominantly negative differences until mid-2020. In contrast, the post-COVID-19 period shows a shift, with higher connectedness in the upper quantile.

Feng et al. (2018) indicate that left-tail correlations among cryptocurrencies are significantly greater than right-tail correlations, with these tail correlations rising after August 2016, suggesting increasing systematic risks. Our findings suggest that before COVID-19, the crypto-mining stocks and cryptocurrencies were more closely connected in the lower quantile, potentially limiting diversification opportunities.

On the other hand, higher connectedness in the upper quantile after COVID-19 suggests a stronger relationship between the two markets, likely reflecting the broader recovery of financial markets from the COVID-19 crisis. Figure 5 shows that the difference in quantile connectedness has returned to pre-COVID levels by 2022. Understanding these dynamics under varying market conditions can assist investors in managing risks and optimizing investment strategies.

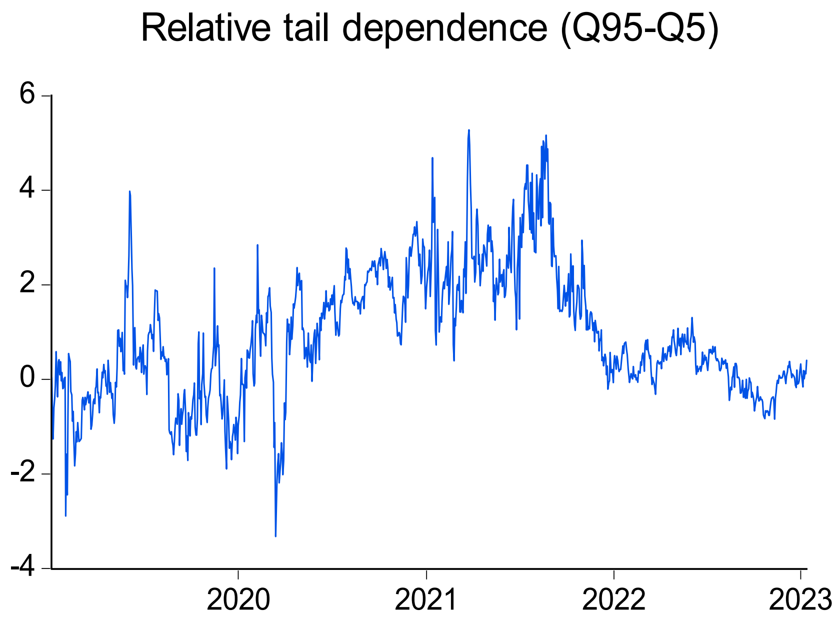


Figure 5. Relative tail dependence ($TSI_{Q=0.95} - TSI_{Q=0.05}$).

We present the net spillover of each variable in Figures 6, 7, and 8 for the median, extreme lower, and extreme upper quantiles, respectively.

Figure 6 indicates that Bitcoin was a net transmitter of shocks before 2021 but became a net receiver afterward. Conversely, HIVE, HUT, CLSK, and BTBT showed the opposite trend. RIOT and MARA consistently acted as net transmitters, while WULF, GREE, NILE, and BTCM were primarily net receivers, with the exception of 2020 during the COVID-19 period. The mid-2021 regime shift also aligns with increased institutional adoption of Bitcoin (e.g., Grayscale, Tesla), while the post-FTX regime reflects a loss of retail confidence, rising regulatory scrutiny, and liquidity fragmentation (Conlon et al., 2023; Yousaf et al., 2023). These findings suggest that the dynamics of spillovers are tied not only to market volatility but also to changing perceptions of Bitcoin's role as a systemic anchor in the crypto-financial network.

Figure 7 reveals that Bitcoin has consistently and predominantly transmitted shocks, with only two periods where it behaves as a net receiver of shocks, around the ends of 2020 and 2022. Moreover, RIOT, MARA, HIVE, and HUT have also been mostly net shock transmitters, whereas CLSK, GREE, and NLE have been net shock receivers. WULF, BTBT, and BTCM have shifted between receiver and transmitter roles.

Figure 8 shows that Bitcoin remains a net transmitter in the extreme upper quantile, with few exceptions. Similar to the lower quantiles, RIOT, MARA, HIVE, and HUT are mainly net transmitters, while CLSK, BTBT, and GREE act as net receivers. WULF, NLE, and BTCM exhibit varying roles over time.

The finding that RIOT and MARA are consistent net shock transmitters can be partly explained by their dominant market capitalization and operational scale in the crypto-mining industry. These firms often serve as benchmarks for investor sentiment in the sector and are more frequently covered in financial media. Their operational models involve significant exposure to energy prices and leverage. It makes them more sensitive to macroeconomic news, which can propagate to the rest of the system. Conversely, firms like GREE, NILE, and BTCM are smaller, more volatile, and often act as net receivers of shocks, likely due to passive investor behavior or lower visibility in market narratives.

These asymmetries may also be linked to speculative market dynamics. During periods of exuberance or panic, investors tend to follow large-cap firms, amplifying spillovers from those firms (herding behavior in cryptocurrency markets, (Youssef, 2022)). Our findings align with theories of information-driven contagion and risk propagation in speculative assets (e.g., Bikhchandani & Sharma, 2000; Danielsson et al., 2012), reinforcing the need to understand firm-level heterogeneity in shock transmission roles.

Our key finding is that Bitcoin has become an increasingly dominant transmitter of shocks to crypto mining stocks, particularly under extreme market conditions. This is most evident in the extreme quantiles. The total connectedness reaches as high as 88%. The asymmetry is particularly notable pre- and post-COVID-19. The left-tail connectedness dominates in the early years, and right-tail connectedness rises afterward. These results are obtained using the quantile connectedness framework of Ando et al. (2022). This enables us to capture tail-dependent spillovers over time. Our findings matter for two reasons. First, they provide strong evidence that Bitcoin does not serve as a safe-haven asset, confirming prior concerns raised by Conlon and McGee (2020) and Klein et al. (2018). Second, the dynamic and quantile-dependent nature of connectedness implies that portfolio risk is highly sensitive to market regimes, especially in times of crisis or exuberance. This insight is essential for institutional investors, risk managers, and policymakers concerned with the systemic risk and fragility of crypto-linked assets.

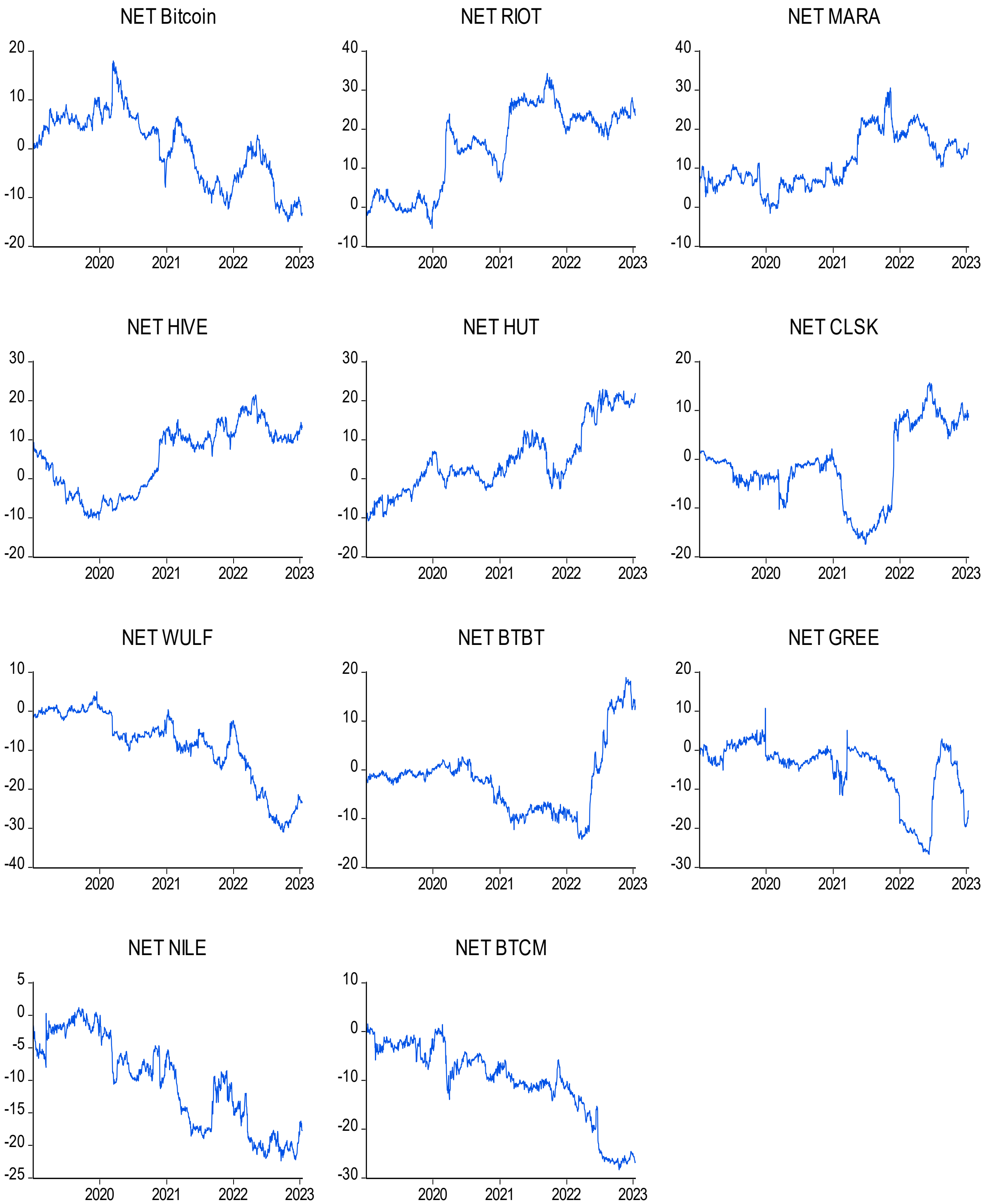


Figure 6. Net spillover at the median quantile (Q=0.50).

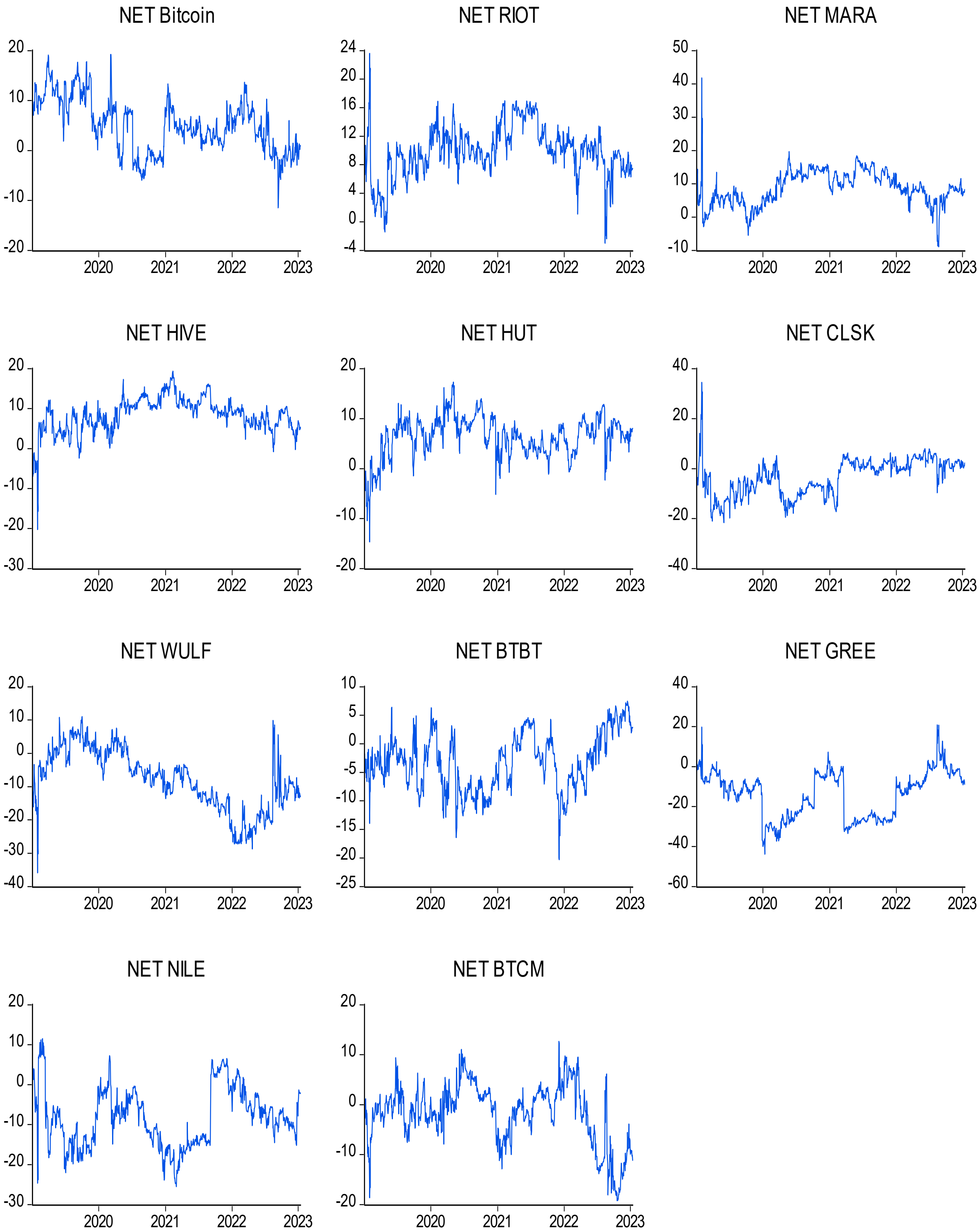


Figure 7. Net spillover at the extreme lower quantile (Q=0.05).

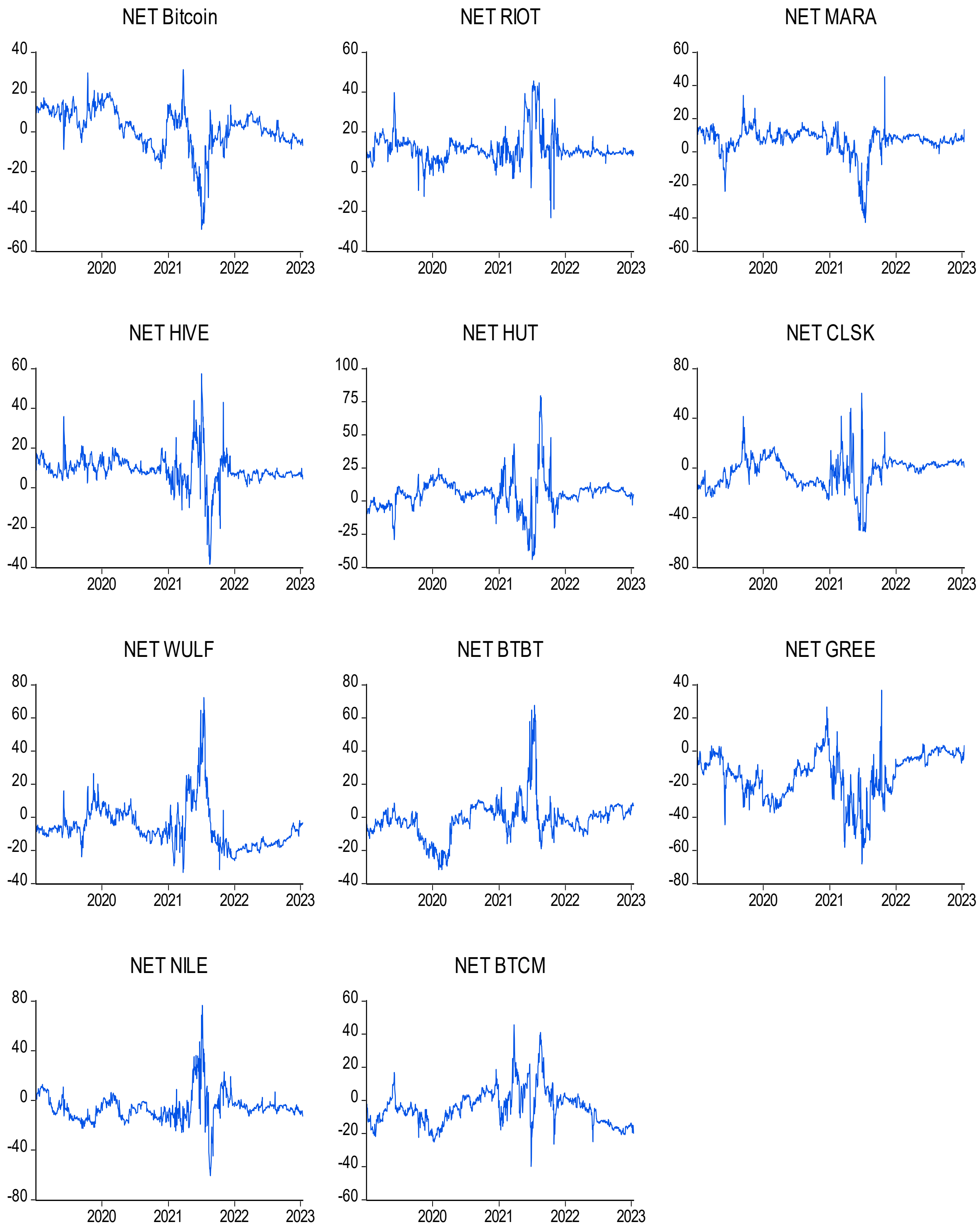


Figure 8. Net spillover at the extreme upper quantile (Q=0.95).

5.4. Implications for portfolio management

These findings have significant implications for portfolio management, guiding diversification and hedging strategies. We analyze this further from the perspective of portfolio management by providing optimal weights and hedging ratios for each asset in Table 6 below.

Before 2021, Bitcoin often acted as a primary transmitter of shocks throughout the market; this dynamic appears to have shifted since. Although crypto mining stocks are not directly tied to Bitcoin like derivatives, they can influence Bitcoin prices through economic channels (Easley et al., 2019).

First, increased demand for mining stocks, often reflecting investor optimism in Bitcoin, can drive up cryptocurrency prices (Yousaf et al., 2024; Anamika et al., 2023). Second, strong performance of mining stocks may signal the market's expectation of rising Bitcoin prices. While halving events can initially pressure mining company profits, they often lead to increased Bitcoin prices due to a reduced supply of newly minted coins (Jo et al., 2020).

Third, mining efficiency can impact Bitcoin prices indirectly by affecting the overall supply of mined coins. As mining efficiency improves, often through advancements in hardware or lower energy costs, miners can produce more Bitcoin at reduced costs (Kristoufek, 2020). If this increased supply is not matched by demand, it could exert downward pressure on Bitcoin prices.

Last, competition in the mining industry also influences Bitcoin prices. The fickle mining behavior, where miners are motivated exclusively by profit and switch between mining coins with compatible consensus algorithms, can lead to a concentration of mining power. This can impact the security and, consequently, the perceived value of Bitcoin (Kwon et al., 2019). While this overview highlights these relationships, further research is needed to fully understand the complex interactions involved.

The theoretical foundation of our study is rooted in key concepts from portfolio theory, particularly diversification and its connection to systemic risk, as articulated by Markowitz (1952). Diversification aims to minimize idiosyncratic risk by optimizing a portfolio of diverse investments. This concept has been extensively examined, with various approaches proposed, including naive diversification, equal risk contribution diversification, and the maximization of the diversification ratio (DeMiguel et al., 2009; Roncalli and Weisang, 2016; Choueifaty et al., 2013).

The effectiveness of diversification is often assessed using correlation-based measures, which can be viewed as a generalization of the connectedness concept introduced by Diebold and Yilmaz (2009). Connectedness measures the interdependence among components of a system and quantifies systemic risk (Diebold and Yilmaz, 2012 & 2014). While diversification emphasizes the reduction of idiosyncratic risk, connectedness focuses on estimating systemic risk components (Maggi et al., 2020). Eigenvalues play a crucial role in both areas, serving as a tool to evaluate diversification and connectedness (Meucci, 2009; Maggi et al., 2020).

In our study, we aim to quantify the optimal weights, hedge ratios, and hedging effectiveness. Optimal weights determine the proportion of each asset in the optimal portfolio, while hedge ratios indicate the quantity of each asset needed to hedge against the risk posed by another. Hedging effectiveness measures how successful each asset is in hedging against the risk of others.

High levels of connectedness present challenges for effective diversification, as they signify stronger interdependencies among assets, making it harder to minimize risk. Conversely, lower connectedness levels facilitate better diversification opportunities, aligning with the traditional diversification goal of risk reduction. Therefore, we aim to elucidate the intricate relationships among these pivotal concepts in portfolio management and risk assessment, offering insights into optimal portfolio construction and risk mitigation strategies (Torrente & Uberti, 2021).

Table 6 presents the measures for the pairwise portfolios, comprising the ten crypto-mining stocks paired with Bitcoin. The optimal weights of the portfolio indicate the proportion of each asset in the portfolio, with some stocks carrying higher weights than others. For instance, Bitcoin/HIVE, Bitcoin/NILE, and Bitcoin/MARA have the highest optimal weights of 0.92, 0.90, and 0.92, respectively. These high optimal weights suggest that Bitcoin has a greater potential for higher returns and lower risks in a portfolio when paired with HIVE, NILE, and MARA. In contrast, Bitcoin/GREE has the lowest optimal weight of 0.52, where Bitcoin should constitute 52% of the portfolio; comparatively, Bitcoin is less favorable in a portfolio with GREE to yield an optimal combination of return and risk.

The hedge ratios indicate how much of each crypto-mining stock is needed to hedge against the underlying risk of Bitcoin. These ratios vary across crypto-mining stocks, with Bitcoin/CLSK and Bitcoin/WULF having the lowest ratios of 0.12 and 0.10, respectively, and Bitcoin/RIOT having the highest ratio of 0.36.

This means that a $1 long position in Bitcoin can be hedged with a short position of 12 cents in CLSK or 10 cents in WULF. Conversely, hedging a $1 long position in Bitcoin requires a 36-cent short position in RIOT. The low hedging ratio in this situation indicates that just a small holding of this company stock is required to protect against the risk of Bitcoin, whereas the higher ratio indicates that more shares are required for hedging. This variation in hedge ratios reflects the differing effectiveness of crypto-mining stocks in mitigating Bitcoin's risk.

Finally, the hedging effectiveness measure indicates how successful each crypto-mining stock is in hedging against Bitcoin's risk. The effectiveness measures range from 0.03 for Bitcoin/HIVE to 0.33 for Bitcoin/WULF. It is noteworthy that Bitcoin/WULF has the highest hedging effectiveness measure, indicating that WULF is the most effective stock for hedging against Bitcoin. Moreover, Yousaf and Ali (2021) and Akhtaruzzaman et al. (2020) also used optimal weights and hedge ratios to make recommendations on the portfolios of stocks with Bitcoin. These measures can assist investors in optimizing their cryptocurrency investment portfolios, enabling them to better manage risk and enhance returns based on Table 6.

While lower hedge ratios may suggest more efficient risk sharing, these findings must be interpreted with caution. In practice, the effectiveness of a hedge also depends on trading costs, liquidity, and execution feasibility. Some crypto mining stocks exhibit low liquidity and high volatility, which may reduce the practical appeal of theoretically optimal hedge positions (Koutmos et al., 2021). However, our interpretation is consistent with findings in the literature showing that equities can effectively diversify crypto risks (Dunbar & Owusu-Amoako, 2022). Furthermore, our results have not been benchmarked against simpler alternatives such as equal-weighted portfolios or shrinkage estimators, which could provide useful reference points for investors. Future research could extend this analysis by comparing performance across hedging models.

Table 6. Portfolio management implications.

	Optimal Weights ($W_{xy,t}$)	Hedge Ratios ($\beta_{xy,t}$)	Hedging Effectiveness (HE)
Bitcoin/RIOT	0.89	0.36	0.04
Bitcoin/MARA	0.92	0.32	0.04
Bitcoin/HIVE	0.92	0.37	0.03
Bitcoin/HUT	0.85	0.34	0.04
Bitcoin/CLSK	0.84	0.12	0.13
Bitcoin/WULF	0.65	0.10	0.33
Bitcoin/BTBT	0.79	0.16	0.2
Bitcoin/GREE	0.52	0.12	0.18
Bitcoin/NILE	0.90	0.11	0.06
Bitcoin/BTCM	0.70	0.15	0.21

Note: W-weights, β-hedge ratio, and HE-Hedging effectiveness. RIOT-Riot Platform Inc., MARA- Marathon Digital Holdings Inc., HIVE-HIVE Blockchain Technologies Ltd., HUT- Hut 8 Mining Corp, CLSK- CleanSpark Inc., WULF-TeraWulf Inc., BTBT- Bit Digital Inc., GREE- Greenidge Generation Holdings Inc., NILE- BitNile Holdings Inc., and BTCM- BIT Mining Limited.

For a robustness check of the median-based quantile connectedness approach, we also perform a conventional mean-based connectedness analysis using Diebold and Yilmaz's (2012) methodology. The results are detailed in Table A1 in the Appendix.

6. Conclusions

In conclusion, despite the challenges and risks faced by the cryptocurrency market, it continues to be a relevant and significant player in the financial landscape, as evidenced by its substantial market capitalization of $1.05 trillion and the growing number of global individual cryptocurrency users. Our study on the extreme connectedness between Bitcoin and crypto-mining stocks contributes to the literature on the relationship between cryptocurrencies and stock markets, as well as the literature on commodity markets and commodity-producing company stocks. We employ a quantile-connectedness technique to quantify the connectedness between Bitcoin and crypto-mining stocks under different market conditions, providing insights into the potential opportunities and risks associated with these assets.

The results indicate that the system we study is highly interconnected, and a shock can propagate strongly, albeit in different directions and strengths, throughout the system. The assets with the highest connectedness to the system are RIOT and Bitcoin, indicating that they are the most influential within the system. Moreover, the spillover effects are more pronounced during extreme market conditions than under normal conditions. The high levels of connectedness in both extreme quantiles indicate a higher level of interdependence between the variables, which has implications for financial stability and systemic risk. Consequently, monitoring the relationship between Bitcoin and crypto-mining stocks is crucial for informed investment decisions and effective risk management.

These findings make several contributions to the literature. First, they extend research on financial connectedness by applying a quantile-based framework to crypto assets, offering a richer understanding of how spillovers behave under different market regimes. Second, they provide evidence against the notion of Bitcoin as a safe-haven asset, aligning with and reinforcing prior critiques (e.g., Conlon & McGee, 2020). Third, by distinguishing the connectedness patterns in the upper and lower tails, we offer practical implications for investors seeking to manage tail risks and for regulators monitoring systemic vulnerabilities in crypto-linked markets.

Overall, our study enhances the understanding of systemic risk transmission in the digital asset space and underscores the importance of using distribution-sensitive tools when analyzing volatile and non-linear financial markets like cryptocurrencies (Dunbar & Owusu-Amoako, 2022).

6.1. Policy implications

Our findings reveal a high degree of interconnectedness between Bitcoin and crypto-mining stocks, particularly during periods of extreme market conditions. This has important implications for policymakers and regulators. Current policies often do not account for the asymmetric nature of financial spillovers in cryptocurrency markets. There is a need to develop regulatory frameworks that incorporate systemic risk assessment tools tailored to the unique characteristics of digital assets. The high connectedness of the system necessitates regulatory oversight to ensure market stability, alongside the development of policies that address systemic risks related to spillover effects.

To address these gaps, policymakers should promote enhanced market transparency by mandating consistent disclosure requirements for crypto-mining firms. Regulatory bodies should also implement stress-testing mechanisms that evaluate the resilience of crypto-related financial instruments during tail events. Establishing guidelines for diversification and portfolio exposure limits can reduce the risk of systemic shocks spreading across asset classes. Furthermore, coordinated efforts between financial regulators, crypto exchanges, and institutional investors are required to develop early-warning systems and risk-monitoring dashboards. These measures would improve investor confidence, contribute to market stability, and enhance the credibility of cryptocurrency markets.

Investors should consider the overall connectedness of the system when making investment decisions regarding Bitcoin and crypto-mining stocks. Given that the total connectedness is 44.66%, a shock in one variable is likely to affect others in the system. Therefore, it is optimal for investors to diversify their portfolios to minimize the risks and avoid potential losses due to spillover effects. Policymakers should encourage investors to do so and, in addition, promote transparency and accountability in the cryptocurrency and stock markets to reduce the risks associated with spillover effects. Portfolio managers need to closely monitor the interdependence of cryptocurrencies and crypto-mining stocks in the system. In particular, they should diversify their portfolios by investing in assets with low connectedness from the system to minimize spillover risks.

6.2. Limitations and future recommendations

This study has several limitations. First, the analysis is restricted to a selected group of crypto-mining stocks and Bitcoin, which may not fully represent the digital asset ecosystem. The sample period, though extensive, may not capture more recent structural changes in the market post-2023.

Additionally, while the quantile connectedness approach enables capturing asymmetries across market conditions, it remains a reduced-form method and does not directly identify causal mechanisms.

In the future, researchers should consider expanding the scope by including a broader set of cryptocurrencies and related equity instruments to test the generalizability of the findings. Incorporating macroeconomic and geopolitical variables could also shed light on external factors influencing the dynamics of connectedness. Moreover, exploring regional variations in regulation and their impact on connectedness could offer additional insights for global policy development.

Furthermore, employing structural models or machine learning-based causal inference methods may help to better identify the underlying drivers of spillovers. Additionally, while our analysis identifies notable shifts in connectedness patterns, particularly post-2021, we acknowledge the absence of formal structural break tests. Researchers could explore these transitions more rigorously using econometric techniques. These directions will help refine the understanding of interconnected crypto-asset markets and support more informed policy and investment decisions.

Author contributions

Dr. Riaz was responsible for data analysis and methodology. Dr. Yousaf contributed to writing and cross-checking the content. Dr. Li led the writing, review, and finalization of the manuscript.

Use of AI tools declaration

No AI tools were used in the research, data analysis, writing, or editing of this manuscript.

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Conflict of interest

The authors declare no conflict of interest.

Statement of data availability, conflict of interest and funding

The data are downloaded from public sources and are available upon request.

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