

Is the fear-of-missing-out contagious among cryptocurrency miners?

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Highlights

- We examine the problem of mining choice between Litecoin and Dogecoin.
- Surges in Dogecoin price significantly affect mining choices, influencing hashrates.
- Fear-of-missing-out can affect miners, inducing herding-like mining decisions.

Abstract.

This study investigates the relationship between cryptocurrency returns and mining decisions, particularly when there are abrupt price fluctuations, so the fear-of-missing-out (FOMO) effect may exist. We examine Litecoin (LTC) and Dogecoin (DOGE) markets, which share the same cryptographic algorithm so that no additional investment is required when switching from mining one to the other, with only the latter as a ‘meme’ asset. We employ the quantile vector autoregressive connectedness approach to estimate the net directional connectedness between 30-day hashrate log growth rates and log returns in the two markets. Fluctuations in DOGE returns can significantly influence mining choices, particularly during abrupt spikes in DOGE prices. The influence implies that the FOMO effect in the cryptocurrency market can impact miners’ decisions.

Keywords: Blockchain; Cryptocurrency; FOMO; Mining; Meme; Quantile vector autoregressive connectedness

JEL Classification: C58 (Financial econometrics), G11 (Portfolio choice·Investment decisions), G41 (Role and effects of psychological, emotional, and cognitive factors on decision making in financial markets)

1. Introduction

Most classical finance literature in behavioral finance and market microstructure suggests that institutional investors are generally less affected by irrational factors like sentiment, whereas retail investors are more vulnerable. Ofek and Richardson (2003) argue that a higher presence of retail

investors makes it more susceptible to behavioral biases that can result in irrational beliefs. Choi, Jin, and Yan (2013) find that increases in retail ownership are associated with overpricing, whereas this is not the case for institutional investors. With the difference in the degree of behavioral bias and other factors that make institutional investors more competitive, the institutions tend to incorporate news information more quickly (Ben-Rephael, Da, and Israelsen, 2017), making asset prices more efficient and informative (Kacperczyk, Sundaresan, and Wang, 2021), while outperforming retail investors in terms of returns and Sharpe ratio (Hu, Kirilova, Park, and Ryu, 2024).

In the cryptocurrency market, miners share some common characteristics with institutions. Li, Reppen, and Sircar (2024) note that major miners benefit from cheaper electricity and more efficient hardware, providing them with a cost advantage. It has been difficult for cryptocurrency miners to survive the mining competition, which is so intensive that even its sustainability became questionable (Saleh, 2021) without such a cost advantage. These findings suggest that most cryptocurrency miners retain competitiveness by investing significant resources to leverage their extensive expertise and informational advantage, similar to institutional investors. Given this similarity, it is reasonable to expect that miners' investment decisions are comparable to those of institutional investors and, therefore, less prone to irrational trading motivations than non-mining cryptocurrency market traders. This expectation carries more conviction with the findings that institutional investors in conventional markets rarely trade cryptocurrencies (Chen, Lepori, Tai, and Sung, 2022).

However, at least three factors make it unlikely to regard miners as trading rationally as institutional traders do in conventional markets. First, the cryptocurrency market is driven more heavily by irrational factors than other markets, mainly because it is still unclear how to define the 'fundamentals' in this market. Given its short history, academics have only recently started to develop pricing and valuation models for cryptocurrencies (Cong, Li, and Wang, 2021; Liu and Tsyvinski, 2021; Liu, Tsyvinski, and Wu, 2022). Furthermore, although cryptocurrencies can be regarded as a means of payment on platforms for specific economic transactions, as stated by Cong, Li, and Wang (2022), it is often difficult to figure out a concrete and detailed specification of the token economics, which are commonly immature. Hence, it is less likely to find a group of traders pursuing trading based on fundamentals in the cryptocurrency market than in other markets.

Second, miners do their job in a significantly flexible way by organizing open mining pools. As demonstrated by Cong, He, and Li (2022), although individual miners achieve competitiveness by mining collectively as a mining pool, the pool has clear distinctions from firms such as financial institutions. Individual miners can freely diversify their resources across multiple mining pools, similar to workers on on-demand labor platforms, which implies that it is virtually costless for an individual miner to join and quit different mining pools repeatedly. Hence, it may be appropriate to regard mining pools as temporarily clustered groups of individual miners rather than firmly bound organizations such

as institutions. This property suggests that miners have characteristics as traders closer to individuals than institutions.

Third, even when we assume that miners are more informed and rational than non-miners, the increased uncertainty due to irrationality may limit the price-stabilizing ability of miners, depriving the private information miners have of its informational value. Stein (1987) theoretically predicts that when more speculative traders enter a market, price destabilization will follow if the private information held by informed traders is incomplete. Blau, Bowles, and Whitby (2016) support this prediction by empirically demonstrating that speculative traders with lottery preferences can destabilize stock prices. Given the evidence of gambling or lottery preferences among cryptocurrency market participants (Dhawan and Putniņš, 2023; Hackethal, Hanspal, Lammer, and Rink, 2022), miners may also have a limited ability to stabilize prices even when they are informed, and therefore, may not be able to exploit the asymmetry in information and rationality as fully as institutional investors do in conventional markets.

Given these three factors and the similarity between institutions and miners, it would be meaningful to investigate how miners make mining decisions while examining whether irrational factors can affect them. However, this investigation is not readily achievable due to the unique way miners engage in the cryptocurrency market. Miners acquire cryptocurrencies through mining rather than purchasing, and analyzing mining strategy solely through tracking their trading behavior is challenging. Hence, mining-related variables, such as hashrate, should be considered when investigating mining decisions. However, mining-related variables are challenging to analyze due to their susceptibility to various factors, such as electricity price and hardware efficiency (Capponi, Ólafsson, and Alsabah, 2023). Therefore, it is crucial to understand the relationship between mining-related variables and mining decisions before using them as proxies for mining decisions.

This study attempts to circumvent this issue by examining markets where mining decisions can be simplified. Specifically, we choose the Litecoin (LTC) and Dogecoin (DOGE) markets to analyze cryptocurrency miners' decision-making processes. DOGE is the primary currency of the Dogecoin blockchain, which originated as a hard fork from the Luckycoin blockchain, itself a fork from the Litecoin blockchain. Given this blockchain family tree, the Litecoin and Dogecoin blockchains share the same cryptographic algorithm called Scrypt. This identity allows miners to switch between LTC and DOGE or even mine both simultaneously without any significant additional hardware investment or re-optimization. Mining techniques such as LTC-DOGE merged mining, enabling miners to mine both cryptocurrencies simultaneously without additional computational effort, demonstrate this versatility. The seamless transition between the two cryptocurrencies simplifies the decision-making process for miners. Since mining can be carried out in an almost identical environment regardless of the miner's choice of cryptocurrency, miners only need to consider a few factors, such as economic rewards and

mining difficulty.

This simplicity creates a natural laboratory to examine how expected changes in economic rewards affect mining choices by investigating the relationship between cryptocurrency returns and mining-related variables such as hashrate. In this study, we exploit this opportunity to investigate how collective mining decisions in the LTC-DOGE market are related to the corresponding cryptocurrency returns. Given that DOGE is one of the most well-known ‘memecoins,’ whose prices tend to be heavily affected by irrational market behaviors, we focus on how such irrational market behaviors are related to mining decisions. Pairing DOGE with LTC highlights this relationship because LTC is far from the concept of a memecoin, with the Litecoin blockchain developed as a sidechain of the Bitcoin blockchain.

A type of irrational behavior we utilize in this study is investor herding due to the fear of missing out (FOMO), which is commonly cited as a characteristic phenomenon in the cryptocurrency market (Baur and Dimpfl, 2018; Bleher and Dimpfl, 2019; Kakinaka and Umeno, 2022; Kristoufek, 2020; Kulbhaskar and Subramaniam, 2023). Kuchler and Stroebl (2021) define FOMO as the widespread fear that others may be enjoying beneficial experiences that one is missing out on. Given this definition, a characteristic pattern in FOMO-oriented price responses would be its asymmetry, which is biased towards positive news or returns. Saggu (2022) empirically demonstrates that the cryptocurrency markets’ price reaction to social media is primarily driven by FOMO, revealing an asymmetric response pattern in bitcoin price, which significantly reacts only to positive news. Hence, if we can reveal that miners asymmetrically react to cryptocurrency price dynamics, showing notable responses only to significantly positive returns, then this pattern would serve as meaningful evidence of the effect of FOMO on miners’ herding behavior.

If it exists, the asymmetric pattern in miners’ response to price dynamics can be highlighted because miners are not likely to be significant buyers but are prominent sellers in the cryptocurrency market. Since miners participate in the market primarily by selling their inventories, they can lead the bearish price movements, particularly when miners agree on when to sell, and the inventory sales occupy a large proportion of the sell volume in the market. Thus, if miners’ herding behavior is affected by FOMO, a significantly asymmetric lead-lag relationship between cryptocurrency returns and mining investment decisions would exist.

We employ the quantile vector autoregressive (Q-VAR) connectedness approach, proposed by Ando, Greenwood-Nimmo, and Shin (2022) (AGS), to examine the interrelations between cryptocurrency returns and mining decisions. The empirical results suggest that returns can significantly affect mining decisions when there are sudden surges in DOGE price, implying that the FOMO effect in the cryptocurrency market can influence the miners. Although there is no clear and monotonic tendency that cryptocurrency returns lead mining decisions, the NDC index value indicates that the DOGE returns influence the hashrate growth rate exceptionally significantly when DOGE returns are at their peaks. In contrast, the hashrates do not react similarly to LTC returns, suggesting that not every cryptocurrency

induces a FOMO effect. Empirical results reveal that significant increases in LTC prices do not affect miners as much as DOGE price surges do, implying that DOGE as a memecoin has a more significant impact on miners with their abrupt price hikes.

The rest of this paper is organized as follows: Section 2 provides an overview of the sample data collected from the LTC-DOGE market. Section 3 outlines the methodology employed in our empirical analysis, and Section 4 summarizes the empirical findings. Finally, Section 5 concludes the paper.

2. Data

The daily LTC-DOGE hashrate and returns data in this study span 111 months from January 2015 to March 2024. The hashrate for a cryptocurrency represents the rate at which hash operations are performed by all the combined mining hardware working to mine that cryptocurrency. A hash operation involves producing a fixed-size string using a hash function to solve mathematical puzzles for cryptocurrency mining. Given these definitions, we employ LTC and DOGE hashrates as proxies for the amount of resources cryptocurrency miners commit to LTC and DOGE mining, respectively. We collect the hashrate and returns data from BitInfoCharts (<https://bitinfocharts.com>), a comprehensive cryptocurrency data and analysis platform referenced by several previous studies (Basu, Easley, O'Hara, and Sirer, 2023; Garratt and van Oordt, 2023; Malik, Aseri, Singh, and Srinivasan, 2022). Hashrate is measured as the average hashrate (hash/s) per day.

To investigate the relationship between hashrates and returns under a well-balanced setting, we transform the variables uniformly. First, we calculate the 30-day log-difference for each variable. Specifically, for hashrates and returns, we measure the 30-day log growth rates H and log returns R , respectively, as follows:

$$H_{LTC,t} = \ln(h_{LTC,t}/h_{LTC,t-30}), \quad (1)$$

$$H_{DOGE,t} = \ln(h_{DOGE,t}/h_{DOGE,t-30}), \quad (2)$$

$$R_{LTC,t} = \ln(p_{LTC,t}/p_{LTC,t-30}), \quad (3)$$

$$R_{DOGE,t} = \ln(p_{DOGE,t}/p_{DOGE,t-30}), \quad (4)$$

where $h_{i,t}$ and $p_{i,t}$ are the hashrate and price of cryptocurrency i on day t , respectively. We opt for the 30-day period instead of examining daily change rates to capture the evolutionary characteristics of investor decision-making procedures and the FOMO effect (Park, Ryu, and Webb, 2024).

Next, we compute the difference in the growth rates and returns between LTC and DOGE to utilize them as the primary variables as follows:

$$H_{DIFF,t} = H_{LTC,t} - H_{DOGE,t}, \quad (5)$$

$$R_{DIFF,t} = R_{LTC,t} - R_{DOGE,t}. \quad (6)$$

We adopt the differences between the two currencies as the primary variables to consider the fact that miners make choices between the two cryptocurrencies. Figure 1 illustrates the time series dynamics of the differences, as well as the 30-day log growth rates and log-returns.

[Figure 1 about here]

3. Methodology

In this study, we investigate the time-varying connectedness between LTC-DOGE returns and hashrate growth rates to evaluate the influence of returns on mining decisions. We employ the Q-VAR connectedness approach of AGT, who adopt the connectedness analysis framework of Diebold and Yilmaz (2012, 2014). While non-quantile connectedness approaches estimate the effect of an average-sized shock from one variable on another, the Q-VAR approach enables us to estimate the effect of idiosyncratic shocks from one variable on another as the size of the shocks varies. This characteristic is useful in our study because we are interested in how abrupt changes, whose magnitudes are larger than average, influence mining decisions. Furthermore, given the properties of the main variables in this study, the quantile value we set in the Q-VAR approach provides information on the idiosyncratic shocks.

The Q-VAR approach estimates VAR models at a conditional quantile, which we denote as $\tau \in (0,1)$. We follow the procedure of Chatziantoniou, Gabauer, and Stenfors (2021) to employ the Q-VAR connectedness approach using the R package ‘ConnectednessApproach’.¹ The following VAR model is adopted to explain $H_{DIFF,t}$ and $R_{DIFF,t}$ in Equations (5) and (6) as an autoregressive function:

$$\mathbf{y}_t = \boldsymbol{\mu}_{(\tau)} + \sum_{j=1}^p \boldsymbol{\Phi}_{j(\tau)} \mathbf{y}_{t-j} + \mathbf{v}_t, \quad (7)$$

where $\mathbf{y}_t = [H_{DIFF,t} \ R_{DIFF,t}]'$ is a 2×1 vector of endogenous variables, $\boldsymbol{\mu}_{(\tau)}$ is the conditional mean vector for conditional quantile τ , p is the lag length, $\boldsymbol{\Phi}_{j(\tau)}$ is a 2×2 Q-VAR coefficient matrix for the j^{th} lag and conditional quantile τ , \mathbf{v}_t is a 2×1 vector of regression residuals with a 2×2 positive definite variance-covariance matrix, denoted as $\boldsymbol{\Sigma}_{(\tau)}$. The Wold representation of Equation (7) can be expressed as:

$$\mathbf{y}_t = \boldsymbol{\mu}_{(\tau)} + \sum_{j=1}^{\infty} \boldsymbol{\Psi}_{j(\tau)} \mathbf{v}_{t-j}, \quad (8)$$

which is a transformation from a quantile VAR process of order p to its vector moving average representation of infinite order.

We then proceed to an H -step-ahead generalized forecast error variance decomposition (GFEVD) of

¹ <https://github.com/GabauerDavid/ConnectednessApproach>

the endogenous variables to measure the proportion of forecast error variation in an endogenous variable attributable to shocks coming from the other endogenous variable. Following previous studies, CGS and, we set $H = 20$ (Chatziantoniou, Gabauer, and Stenfors, 2021; Gabauer and Stenfors, 2024). With GFEVD, the portion attributable to shocks from the j^{th} endogenous variable for the forecast error variation of the i^{th} endogenous variable can be expressed as:

$$\Psi_{ij(\tau)}(H) = \frac{\Sigma_{ii(\tau)}^{-1} \Sigma_{h=0}^{H-1} (\mathbf{e}_i' \boldsymbol{\Psi}_{(\tau)}(h) \boldsymbol{\Sigma}_{(\tau)} \mathbf{e}_j)^2}{\Sigma_{h=0}^{H-1} (\mathbf{e}_i' \boldsymbol{\Psi}_{(\tau)}(h) \boldsymbol{\Sigma}_{(\tau)} \boldsymbol{\Psi}_{(\tau)}'(h) \mathbf{e}_i)}, \quad (9)$$

where \mathbf{e}_i represents 2×1 vector whose value is one on the i^{th} row and zero otherwise. We then normalize $\Psi_{ij(\tau)}(H)$ in Equation (9) as:

$$\tilde{\Psi}_{ij(\tau)}(H) = \frac{\Psi_{ij(\tau)}(H)}{\sum_{j=1}^2 \Psi_{ij(\tau)}(H)}, \quad (10)$$

so that the conditions $\sum_{i=1}^2 \tilde{\Psi}_{ij(\tau)}(H) = 1$ and $\sum_{j=1}^2 \sum_{i=1}^2 \tilde{\Psi}_{ij(\tau)}(H) = 2$ can be satisfied. The first condition means that the magnitude of the shocks coming from a single endogenous variable sums to one, influencing both the originating variable and the other.

With the result of GFEVD, we compute NDC, which is the difference between the magnitude of shock transmissions from an endogenous variable to the others and vice versa. Based on Equation (10), NDC can be expressed as:

$$NDC_{ij(\tau)}(H) = \tilde{\Psi}_{ij(\tau)}(H) - \tilde{\Psi}_{ji(\tau)}(H), \quad (11)$$

given that there are only two endogenous variables considered in this study. We calculate NDC for $R_{DIFF,t}$ so that a positive (negative) value of NDC indicates the return difference has more (less) significant influence to $H_{DIFF,t}$ compared to the reverse scenario.

4. Empirical analysis

4.1. Connectedness between hashrate growth and return differences

To empirically investigate the relationship between LTC-DOGE hashrates and returns, we first estimate the NDC between the hashrate growth and return differences, $H_{DIFF,t}$ and $R_{DIFF,t}$, for the sample period, based on the Q-VAR approach. We then examine the pattern in the dynamics of the NDC index to determine whether there is evidence that mining decisions are closely associated with cryptocurrency returns. We particularly focus on the NDC dynamics when there are notable fluctuations in returns so that traces of the FOMO effect on mining choices can be identified. If the FOMO effect affects cryptocurrency miners, we expect that cryptocurrency returns will significantly influence mining decisions when there are large return fluctuations.

Figure 2 illustrates the NDC estimation result, which reveals three noteworthy findings. First, there is no clear and monotonic tendency for cryptocurrency returns to lead or follow mining decisions. The fluctuations in the value of NDC indicate that the relative degree of influence between returns and hashrates is time-varying and depends on quantile selection. Second, despite the unclear tendency, NDC tends to have significantly positive values, which means that returns influence hashrates more significantly than vice versa when there is a surge in DOGE returns. As marked with dashed lines in Figure 2, NDC is highest in February 2016, January 2018, and February 2021, particularly for the lowest quantiles at which DOGE returns tend to be significantly higher than LTC returns. Third, at the highest quantiles, for which LTC returns are significantly higher than DOGE returns, NDC is often negative, implying that significant changes in hashrates frequently precede high LTC returns.

[Figure 2 about here]

Although Figure 2 suggests that the relationship between cryptocurrency returns and mining decisions may be affected by return fluctuations, the figure does not provide any statistical evidence for this phenomenon. Hence, we further investigate the relationship between NDC and individual factors, such as the hashrates and returns for both LTC and DOGE, to analyze the factors determining the relationship between returns and mining decisions in more detail. We estimate a set of OLS models using NDC as the dependent variable and hashrates and returns as independent variables. Given the extremely high correlation between $H_{LTC,t}$ and $H_{DOGE,t}$, which is 0.927, we employ the first principal component of the two hashrates, $H_{PC,t}$, which can be interpreted as the overall hashrate growth rate, as an independent variable instead of using hashrates for each cryptocurrency. For returns, we include the individual returns $R_{LTC,t}$ and $R_{DOGE,t}$ as independent variables.

Table 3 presents the regression results. The results highlight three notable characteristics. First, returns tend to influence hashrates more significantly than vice versa when the magnitude of returns is significant. At the 5th percentile, at which $R_{LTC,t}$ tends to be negative and $R_{DOGE,t}$ tends to be positive, the expected value of NDC increases when $R_{DOGE,t}$ increases and $R_{LTC,t}$ decreases. In contrast, at the 95th percentile, at which $R_{LTC,t}$ tends to be positive and $R_{DOGE,t}$ tends to be negative, the opposite is the case. This tendency implies that abrupt cryptocurrency price movements may affect miners' decisions. Second, the effect of the overall hashrate growth rate on NDC is insignificant regardless of the percentile, while the coefficient estimates for the individual cryptocurrency returns are statistically significant for all cases. The difference in significance suggests that the NDC is more closely related to returns than hashrate growth rates.

[Table 3 about here]

To examine the asymmetry in the relationship between NDC and returns in more detail and determine whether the relationship is affected by FOMO, we next conduct another set of OLS estimations while controlling for extreme dynamics with a different approach. Instead of conducting OLS estimations for the 5th and 95th Q-VAR percentiles, we estimate OLS models only for the 50th Q-VAR percentile while employing dummy variables for extreme hashrate growth rates and returns. $R_{LTC5,t}$ and $R_{DOGE5,t}$ have a value of one if the LTC and DOGE returns are at their 5th percentile or below on day t , respectively, and zero otherwise. Similarly, $R_{LTC95,t}$ and $R_{DOGE95,t}$ have a value of one if the LTC and DOGE returns are at their 95th percentile or above on day t , respectively, and zero otherwise. We also construct dummy variables for the first principal component of hashrate growth rates, $H_{PC5,t}$ and $H_{PC95,t}$ in a similar way to control for abrupt fluctuations in hashrate growth rates. As in Table 3, we also consider $H_{PC,t}$, $R_{LTC,t}$, and $R_{DOGE,t}$ as independent variables to control for both the linear relationship and the additional effect of extreme hashrate growth and return fluctuations.

Table 4 presents the regression results. The table demonstrates three interesting features. First, the relationship between NDC and DOGE returns is significantly stronger when there are abrupt surges in DOGE price. The magnitude and sign of coefficient estimates for $R_{DOGE95,t}$ suggest that $R_{DIFF,t}$ influences $H_{DIFF,t}$ more strongly than what is estimated by the linear function of $R_{DOGE,t}$ when $R_{DOGE95,t} = 1$. Although the coefficient estimate for $R_{DOGE5,t}$ implies that the relationship between $R_{DOGE,t}$ and NDC is U-shaped, consistent with Table 3, the overall estimation results suggest that, when $R_{DOGE5,t} = 1$, $R_{DIFF,t}$ does not influence $H_{DIFF,t}$ as strongly as when $R_{DOGE95,t} = 1$. This asymmetric relationship demonstrates a possibility that FOMO affects mining decisions, thereby making miners show herding-like behavior of committing more mining resources following abruptly high returns. Second, the relationship between NDC and $R_{LTC,t}$ is surprisingly different from the one between NDC and $R_{DOGE,t}$. The significantly negative coefficient estimate for $R_{LTC,t}$ and the relatively small coefficient estimate for $R_{LTC95,t}$ suggest that significant LTC returns are not likely to influence the relationship between LTC returns and mining decisions. This result can be interpreted as another evidence of FOMO affecting mining decisions because the result demonstrates that the price surges in a ‘memecoin’ make miners follow but LTC, the non-memecoin, does not reveal such influence. Third, the hashrate growth rate is not significantly related to NDC, which is consistent with Table 3. This irrelevance again implies that the interrelation between returns and mining decisions is mostly due to return dynamics, not changes in mining decisions.

[Table 4 about here]

Overall, the empirical results suggest that the LTC-DOGE miners adjust their mining decisions

following return dynamics, particularly when there are surges in DOGE price. Furthermore, the significant influence of large price fluctuations, which is asymmetric so that miners react more sensitively to price surges than drops, suggests that FOMO is one of the factors behind the herding-like mining decisions.

4.2. Connectedness between hashrate growth difference and individual returns

Although the NDC between hashrate growth and return differences demonstrates the overall influence across returns and mining decisions, further investigations are required to determine how each cryptocurrency is interrelated with the miners' decision-making process, as proxied by the hashrate growth difference. Since DOGE has started attracting much more attention from cryptocurrency traders in recent years, whereas LTC has a longer and more stable history, there may be noteworthy patterns regarding how the returns of LTC and DOGE individually affect mining decisions over time. Hence, we conduct another Q-VAR connectedness estimation for three dependent variables, which are $R_{LTC,t}$, $R_{DOGE,t}$, and $H_{DIFF,t}$. After the connectedness estimation, we calculate the NDC for two pairs of dependent variables: $(R_{LTC,t}, H_{DIFF,t})$ and $(R_{DOGE,t}, H_{DIFF,t})$. Since we select two dependent variables out of three for each pair, we refer to the connectedness measure as net pairwise directional connectedness (NPDC), following Chatziantoniou, Abakah, Gabauer, and Tiwari (2021). A comparison of the NPDCs for the two pairs enables an examination of how individual cryptocurrency returns interact with mining decisions, particularly during periods of abnormally high returns.

Figure 3 illustrates the NPDC estimation results for each cryptocurrency return, presenting three interesting features. First, no deterministic influential hierarchy is found between individual cryptocurrency returns and hashrate differences. The direction of net directional connectedness varies across different periods and quantiles, consistent with Figure 2. Second, the significant influence of returns on hashrate differences during return peaks is not simultaneously observed in both cryptocurrencies but alternates between them. Among the three periods in which there is a notable increase in NDC in Figure 2, the first two are accompanied by comparable increases in NPDC for the $(R_{LTC,t}, H_{DIFF,t})$ pair, whereas the last one coincides with a surge in NPDC for the $(R_{DOGE,t}, H_{DIFF,t})$ pair. A possible explanation is that the cryptocurrency that ignites FOMO changes over time. During the 2016 and 2018 return peaks, LTC was a hotter issue in the cryptocurrency market, while traders' attention on DOGE was still premature. In 2021, however, DOGE was gathering much more attention due to events such as propagation by Elon Musk. Under these circumstances, high LTC returns could significantly affect mining decisions in 2016 and 2018, whereas high DOGE returns may have influenced miners in 2021. Third, NPDCs slightly tend to be positive (negative) when returns are significantly positive (negative). In both panels in Figure 3, the heat maps tend to be red-colored for the

highest quantiles but blue-colored for the lowest quantiles. This asymmetric pattern supports the hypothesis that FOMO-induced hypes make miners follow the high returns.

[Figure 3 about here]

As in Section 4.1, we next examine the factors of the interrelationship between returns and hashrates in more detail by estimating OLS models, employing NPDC as the dependent variable and individual returns and hashrates as independent variables. Table 5 summarizes the regression results. The results present three noteworthy findings. First, similar to Table 3, high individual cryptocurrency returns make the returns influence mining decisions more strongly. This result supports the finding in Section 4.1 that miners tend to follow high returns. Second, compared to Table 3, the asymmetry in the magnitude of coefficient estimates across quantiles is more evident, particularly for DOGE, backing the idea that the effect of returns on the relationship between returns and mining decisions is asymmetric due to FOMO. Third, being different from Table 3, $H_{PC,t}$ is found to be significantly related to NPDC, suggesting that adding or removing mining resources committed to a cryptocurrency may affect the interaction between returns and mining decisions. The significantly positive coefficient estimate for $H_{PC,t}$ at the 95th percentile for LTC suggests that opportunistic newcomers in the mining pool can be more sensitive to returns.

[Table 5 about here]

Finally, we further investigate the asymmetry in the relationship between NPDC and returns by estimating another set of OLS models, which include dummy variables for heavy hashrate growth rate and return fluctuations as independent variables, as in Table 4. Table 6 demonstrates the regression results, which reveal two notable features. First, the results further support the idea that the asymmetric relationship between NDC and $R_{DIFF,t}$ in Section 4.1 mostly stems from $R_{DOGE,t}$ rather than and $R_{LTC,t}$, consistent with Table 4. Even when we control for the linear factors $H_{PC,t}$, $R_{LTC,t}$, and $R_{DOGE,t}$ in Columns (2) and (4), the gap between the magnitude of coefficient estimates for $R_{DOGE5,t}$ and $R_{DOGE95,t}$ is more significant when compared to the corresponding columns in Table 4. This asymmetry provides evidence that FOMO affects mining decisions and makes miners follow high returns. Second, consistent with Table 5 but inconsistent with Table 4, the hashrate growth rate is significantly related to NPDC, particularly with abrupt changes in hashrates. The significant but complex relationship between NPDC and hashrate growth rate suggests a need to examine the relationship between hashrate growth and mining decisions in more detail.

[Table 6 about here]

In summary, the results in this section provide evidence that FOMO may influence cryptocurrency miners, making them re-optimize their mining resources while actively following return dynamics. This tendency intensifies particularly when the DOGE price exhibits an abrupt increase, and this asymmetry suggests that FOMO is the reason why miners can make herding-like mining decisions. In contrast, surges in LTC prices do not tend to induce such behavior from miners, implying that memecoins such as DOGE can have more influence on miners when their prices demonstrate explosive movements.

4.3. Subperiod analysis

In Section 4.2, Figure 3 demonstrates that the significant influence of returns on mining decisions during return peaks is not simultaneously observed in both cryptocurrencies but alternates between them. The figure suggests that, among the three return peaks with a notable increase in NDC, the first two are primarily driven by LTC returns, whereas the last one follows DOGE returns. The difference in the primary driver implies that the relationship between returns and hashrates may change over time. Thus, we conduct a subperiod analysis to investigate whether the relationship between NDC and other variables differs significantly across subperiods.

To define subperiods that meet the objective of this study, we approximate the degree of cryptocurrency traders' attention to each cryptocurrency, which can be regarded as a prerequisite for FOMO, by employing the number of tweets for LTC and DOGE as proxies. This choice is based on the fact that the number of tweets is used in finance literature as a proxy for investor attention (Benedetti and Kostovetsky, 2021; Cookson, Lu, Mullins, and Niessner, 2024) and the virality of returns (Chen and Hwang, 2022). We retrieve the daily number of tweets for the two cryptocurrencies from BitInfoCharts. Figure 4 illustrates the time-series dynamics of the daily tweet counts for each cryptocurrency as well as their log-ratio, revealing two noteworthy characteristics. First, the tweet counts for LTC and DOGE show evident peaks at different points in time. The number of LTC-related tweets surges at the beginning of 2018, while the number of tweets about DOGE shows a tremendously high peak at the beginning of 2021. Interestingly, both peaks coincide with the periods highlighted in Figure 3. Second, with the two peaks, the time-series dynamics of the daily tweets log-ratio can be divided into three phases: the first subperiod with a negative ratio from January 2015 to the beginning of 2017, the second subperiod with a positive ratio from 2017 to the beginning of 2021, and the last subperiod with a negative ratio. The alternating signs imply that LTC gathered more trader attention than DOGE until 2017, but then DOGE retook popularity in 2021.

[Figure 4 about here]

Given the characteristics in Figure 4, we define subperiods based on the dates of structural breaks in the number of daily tweets for the two cryptocurrencies. We assume that there is a single break for each cryptocurrency and locate the breakpoints by employing the Bai-Perron approach using the R package ‘strucchange’.² The structural break analysis indicates that the breakpoints for the amounts of LTC and DOGE are June 2, 2017, and January 27, 2021, respectively, which are dates closely related to the peaks in the daily tweet counts. Based on this result, we define the three subperiods as follows: January 1, 2015, to June 1, 2017; June 2, 2017, to January 26, 2021; and January 27, 2021, to March 31, 2024. For each subperiod, we estimate the regression model used in Tables 4 and 6 to investigate whether the relationship between NDC and related variables changes across subperiods. For brevity, we only consider the extended model, which includes dummy variables for $H_{PC,t}$, $R_{LTC,t}$ and $R_{DOGE,t}$, as well as $H_{PC,t}$, $R_{LTC,t}$, and $R_{DOGE,t}$ as independent variables.

Table 7 presents the regression results, which demonstrate three notable features. First, the significantly asymmetric relationship between NDC and $R_{DOGE,t}$ is mostly attributable to the last subperiod, which is the period after traders’ attention to DOGE exploded in January 2021. The coefficient estimate for $R_{DOGE95,t}$ is significantly positive in Subperiod #3 but insignificant in Subperiod #2 and significantly negative in Subperiod #1. Furthermore, the coefficient estimate for the linear term $R_{DOGE,t}$ is significant for Subperiods #1 and #2 but loses its significance in Subperiod #3, implying that the relationship between NDC and $R_{DOGE,t}$ has become more nonlinear in recent periods. These dynamics suggest that the FOMO towards surges in DOGE price has evolved over the sample period and has become significant only recently. Second, the evidence of asymmetry in the relationship between NDC and $R_{LTC,t}$ is weaker for all sample periods, which is consistent with Tables 4 and 6. Third, hashrate growth rate, $H_{PC,t}$, does not reveal any significant relationship with NDC for all sample periods, implying that hashrate growth is not a major determinant of the interaction between returns and mining decisions, as shown in Section 4.1.

[Table 7 about here]

The results of the subperiod analysis again suggest that the herding-like mining decisions of LTC-DOGE miners are attributable to the FOMO towards significant DOGE returns. The results also imply that the influence of FOMO has been particularly intense in the recent period, especially since the sudden increase in traders’ attention to DOGE in 2021. These findings further support the idea that FOMO can be contagious among cryptocurrency miners, particularly if an intense FOMO is ignited in the market following huge increases in prices and traders’ attention.

² <https://cran.r-project.org/web/packages/strucchange>

4.4. NDC and NPDC as functions of Q-VAR quantile

The arguments in the sections above heavily rely on the findings regarding the asymmetry in the relationship among the variables. We demonstrate that significant DOGE returns influence mining decisions more than significant LTC returns do, and positive DOGE returns influence affect miners more than negative DOGE returns do. We can further verify these asymmetric patterns by regarding NDC and NPDC as functions of the Q-VAR quantile. If we express NDC as a function of the Q-VAR quantile, a negative slope will indicate that NDCs are higher when DOGE returns are larger than LTC returns, which suggests that large DOGE returns affect miners more than large LTC returns do. Hence, the negative slope can be regarded as evidence that miners are more affected by meme coin returns, which are more likely to induce FOMO. Furthermore, if we define NPDC as a function of the Q-VAR quantile, a positive slope can be interpreted as a sign that NPDCs are larger when cryptocurrency returns are significantly positive, implying that positive returns influence mining decisions more than negative returns, which is a signal that there is a FOMO towards significantly positive returns behind the influence. Hence, if there exists statistical evidence that NDC and NPDC are negatively and positively sloped functions of the Q-VAR quantile, respectively, the evidence will again support the idea that FOMO affects miners.

Based on this idea, we conduct daily OLS regressions of NDC and NPDC on the Q-VAR quantile to investigate whether there exist slopes as expected. For the regressions, we first consider the following model:

$$(NDC) \text{ or } (NPDC) = \alpha + \beta \cdot (Quantile) + \varepsilon, \quad (12)$$

where β can be interpreted as the slope coefficient. Hence, once we estimate the daily β for the entire sample period, we conduct a t -test to determine whether β is significantly different from zero. Additionally, we estimate the following quadratic model to determine whether the relationship between NPDC and cryptocurrency returns is nonlinear:

$$(NPDC) = \alpha + \beta_0 \cdot (Quantile) + \beta_1 \cdot (Quantile)^2 + \varepsilon, \quad (13)$$

from which we take β_1 as the curvature coefficient. A significantly positive estimate for β_1 will indicate that the influence of cryptocurrency returns on mining decisions is significantly larger for higher quantiles, which can be another evidence of the impact of FOMO on miners. Figure 5 demonstrates the time-series dynamics of β and β_1 for NDC and NPDCs.

[Figure 5 about here]

Table 8 presents the t -test results for the slop and curvature coefficient estimates, highlighting four noteworthy characteristics. First, the slope coefficient β is significnatly negative for NDC, indicating

that NDCs are higher when DOGE returns surpass LTC returns. This negative slope suggests that substantial DOGE returns influence miners more than substantial LTC returns. Second, the slope coefficient β is significantly positive for NPDCs, indicating that positive returns have a greater impact on mining decisions than negative returns. Third, the curvature coefficient β_1 is significantly positive for NPDCs, implying that the effect of cryptocurrency returns on mining decisions is more pronounced at higher quantiles. Fourth, the signs of the slope and curvature coefficient estimates remain mostly consistent across subperiods, especially for Subperiods #2 and #3. However, the signs differ for some models in Subperiod #1, suggesting that the impact of FOMO on mining decisions became significant after cryptocurrencies attracted attention from a larger group of traders.

[Table 8 about here]

Overall, the slope and curvature coefficient estimates suggest that asymmetric relationships among NDC, NPDC, and quantile exist as explained above. The asymmetric relationships imply that the FOMO from the DOGE market influences mining decisions, particularly when DOGE returns are significantly high. Along with the empirical results in previous sections, the relationships serve as evidence that FOMO can induce herding-like behavior in cryptocurrency miners.

5. Conclusion

This study explores the relationship between collective mining decisions in the LTC-DOGE market and the corresponding cryptocurrency returns. We utilize the quantile vector autoregressive time-frequency connectedness approach to analyze the connections between cryptocurrency returns and hashrates, using hashrates as a proxy for mining decisions. The findings indicate that DOGE returns can have a significant impact on mining decisions during sudden price surges, suggesting that the FOMO effect in the cryptocurrency market can influence miners. In contrast, hashrates do not respond similarly to LTC returns, indicating that not all cryptocurrencies trigger a FOMO effect.

We present three promising avenues for future research. First, the FOMO effect, which may influence cryptocurrency miners even when no additional investment is required, could be further explored to understand how the level of additional investment changes this influence. If it can be empirically demonstrated that cryptocurrency miners may purchase or replace their hardware, to some extent, following significantly high returns, this behavior could serve as more robust evidence of the FOMO effect on miners. Second, it would be of great significance if future research could ascertain whether the FOMO effect can delay miners' selling activities. While this study examines the relationship between returns and mining activities, we do not provide evidence that returns also influence the trading activities of miners. Therefore, future research could bridge this gap by investigating the relationship

between returns and miners' sell volume. Third, as suggested in Section 4.2, the relationship between hashrate growth and mining decisions presents a rich area for further investigation.

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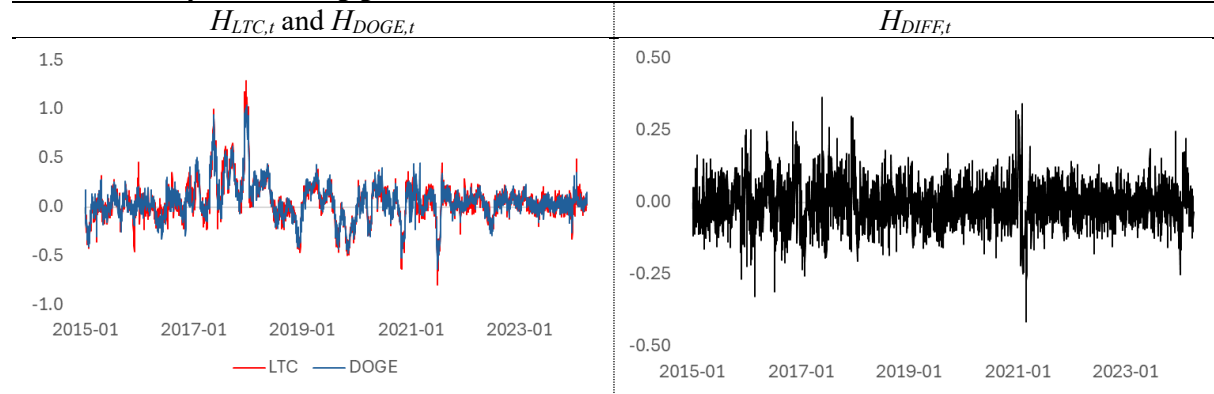
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Figure 1. Time-series dynamics of LTC-DOGE hashrate and 30-day returns

Note. This figure depicts the time-series dynamics of 30-day hashrate log growth rate, H , and 30-day returns, R , for Litecoin (LTC) and Dogecoin (DOGE), as well as their differences, during the sample period from January 2015 to March 2024. Panel A illustrates the dynamics of the 30-day hashrate log growth rate of two cryptocurrencies, as well as their difference. Panel B depicts time-series dynamics of the 30-day cumulative log-returns and their differences.

Panel A. 30-day hashrate log growth rate H



Panel B. 30-day log-returns R

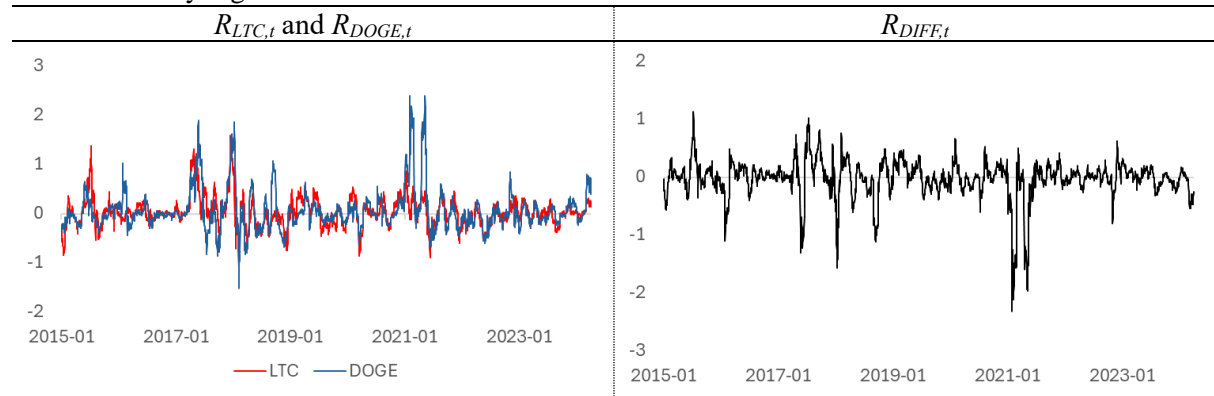
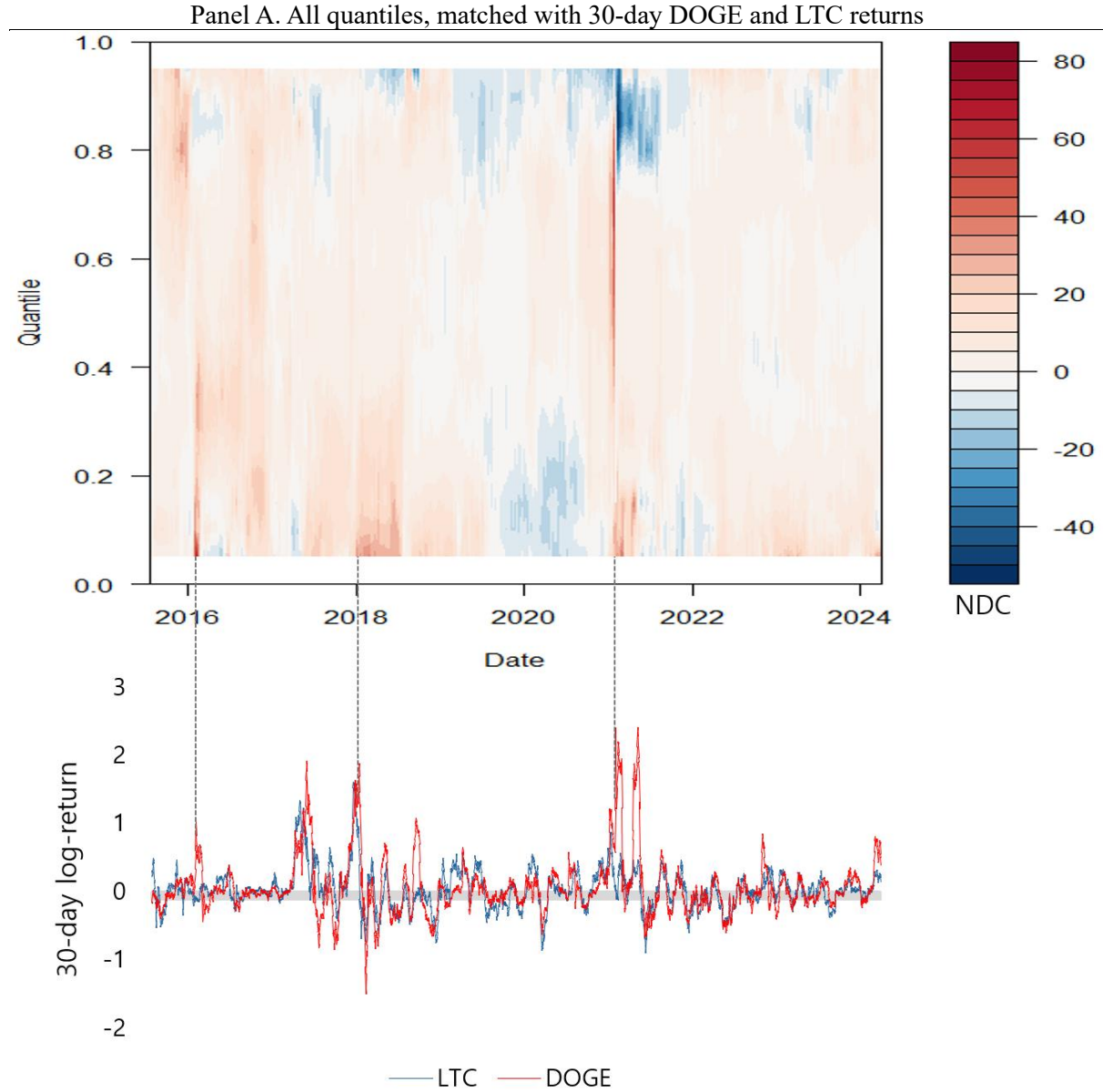


Figure 2. Net directional connectedness between LTC-DOGE hashrate growth and return

Note. This figure depicts the net directional connectedness (NDC) indices between 30-day hashrate log growth rate difference, $H_{DIFF,t}$, and 30-day log return difference, $R_{DIFF,t}$, for different quantiles during the sample period from January 2015 to March 2024. NDC is estimated following the net pairwise directional connectedness estimation procedure of Chatziantoniou, Abakah, Gabauer, and Tiwari (2021). Positive (negative) value of NDC means R_{DIFF} have more (less) significant influence on H_{DIFF} than vice versa. Panel A illustrates the overall dynamics of NDC over time and quantiles. Panel B–D depicts the time-series dynamics of NDC for the 5th, 50th, and 95th percentiles, respectively.



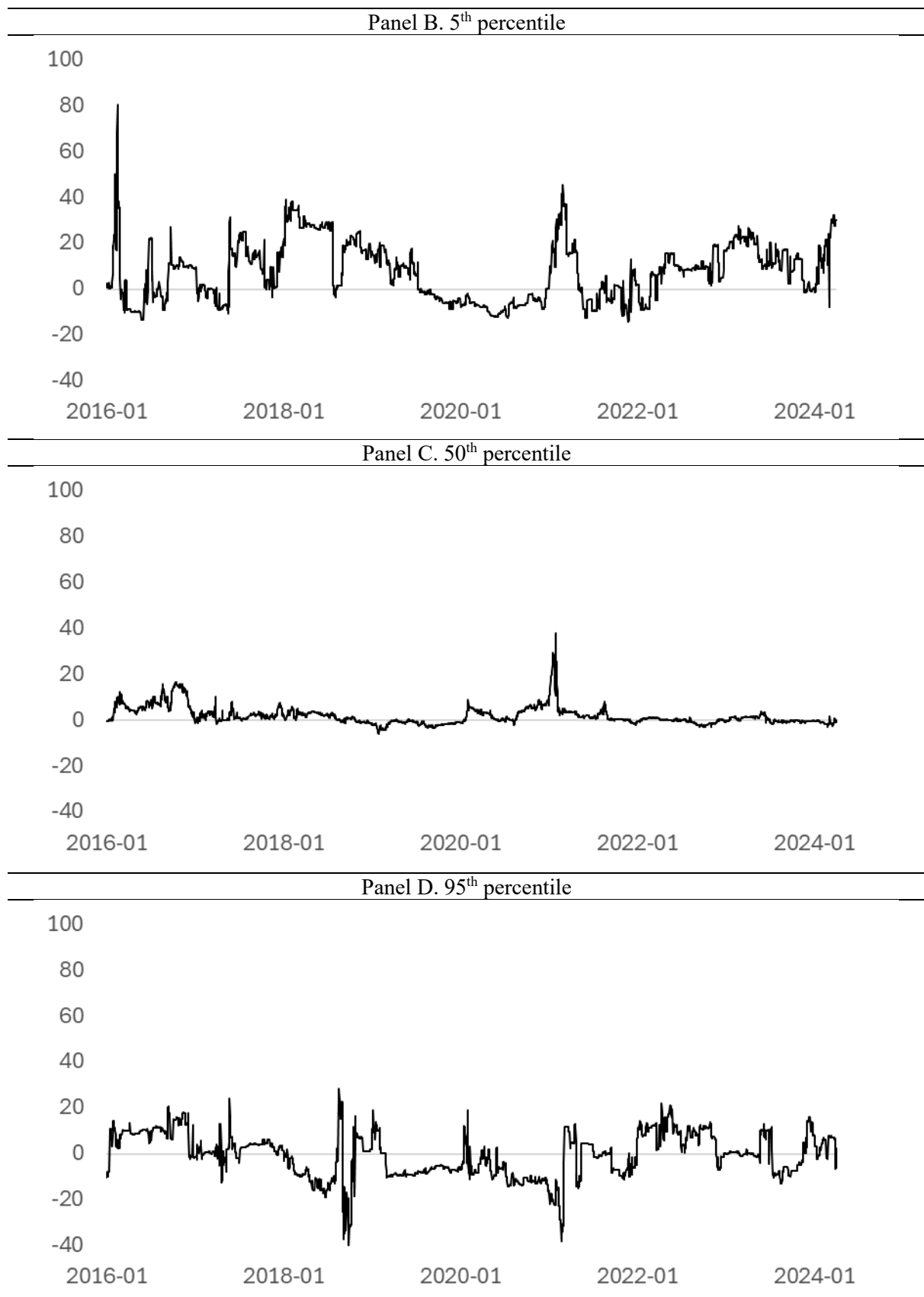


Figure 3. Net pairwise directional connectedness between hashrate growth difference and individual cryptocurrency returns

Note. This figure depicts the net pairwise directional connectedness (NPDC) indices among three dependent variables, which are 30-day hashrate log growth rate difference, $H_{DIFF,t}$, and 30-day log return of LTC and DOGE, $R_{LTC,t}$ and $R_{DOGE,t}$, respectively, for different quantiles during the sample period from January 2015 to March 2024. NPDC is estimated following the estimation procedure of Chatziantoniou, Abakah, Gabauer, and Tiwari (2021). Positive (negative) value of NPDC means R have more (less) significant influence on H than vice versa. Panels A and B illustrate the overall dynamics of NPDC over time and quantiles for LTC and DOGE, respectively.

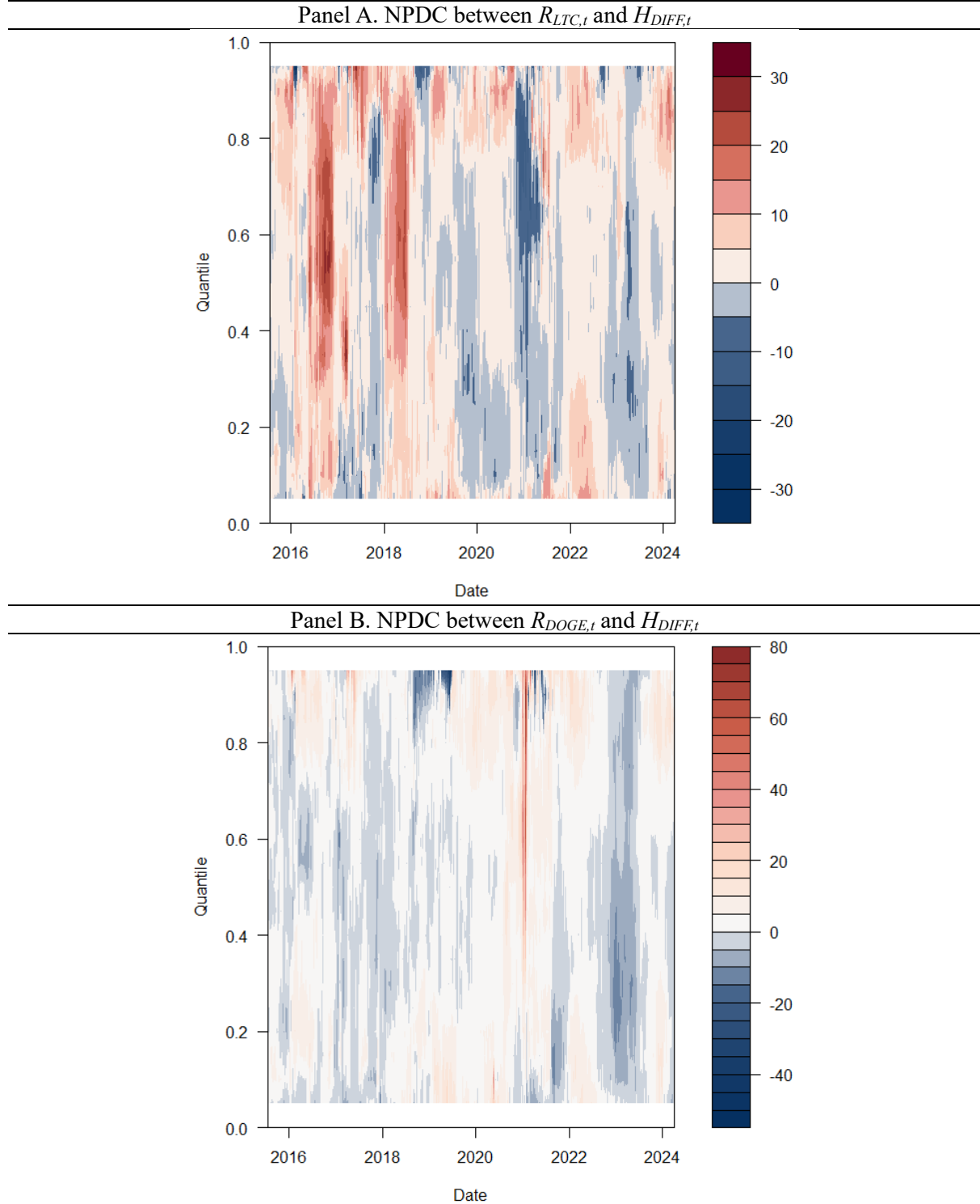


Figure 4. Daily amounts of cryptocurrency-related tweets

Note. This figure illustrates the daily amounts of tweets that are related to the cryptocurrencies employed in this study. Panels A and B demonstrate the daily amounts of LTC- and DOGE-related tweets, respectively. Panel C shows the time-series dynamics of the daily log-ratio, $\ln[(\# \text{ of LTC-related tweets})/(\# \text{ of DOGE-related tweets})]$.

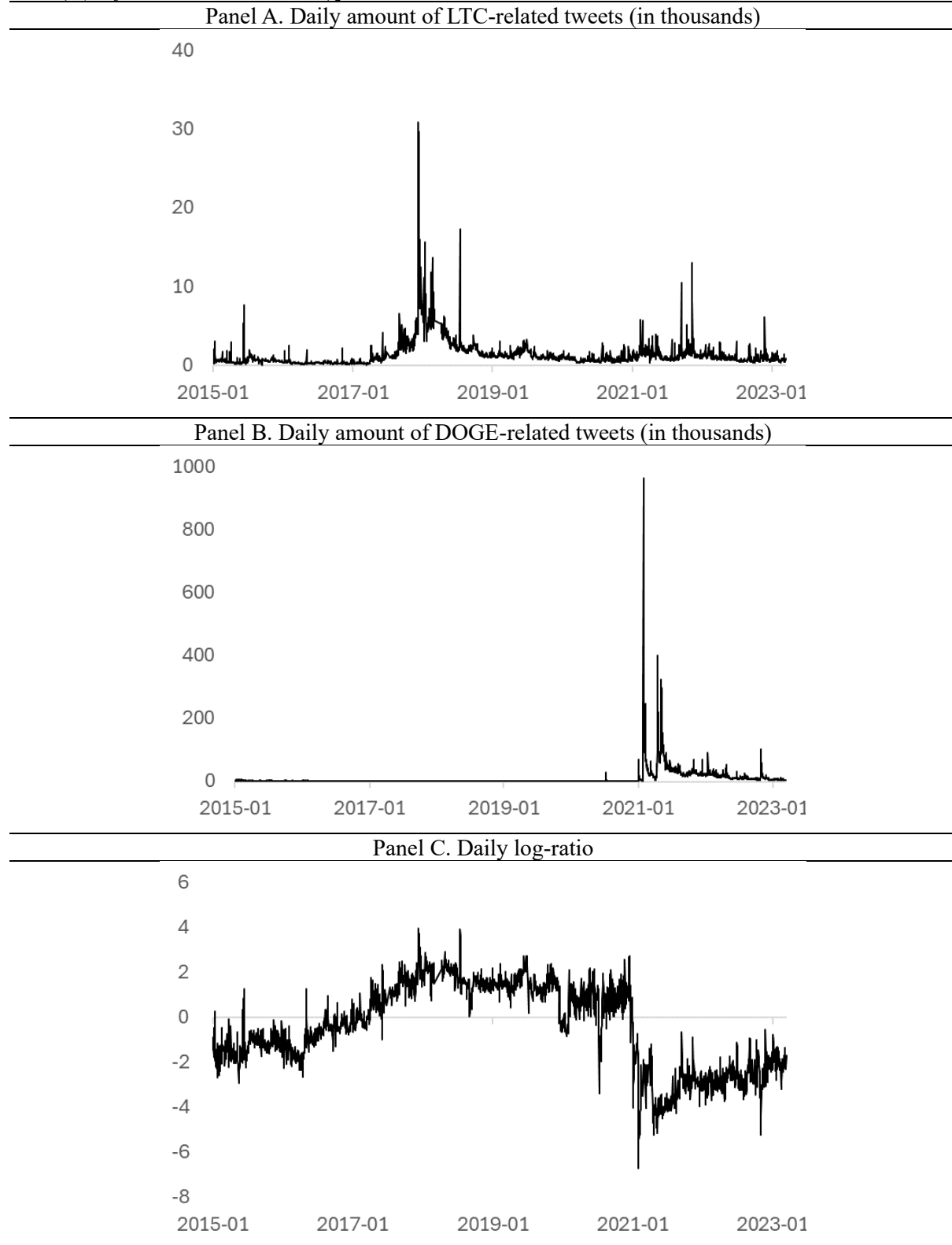
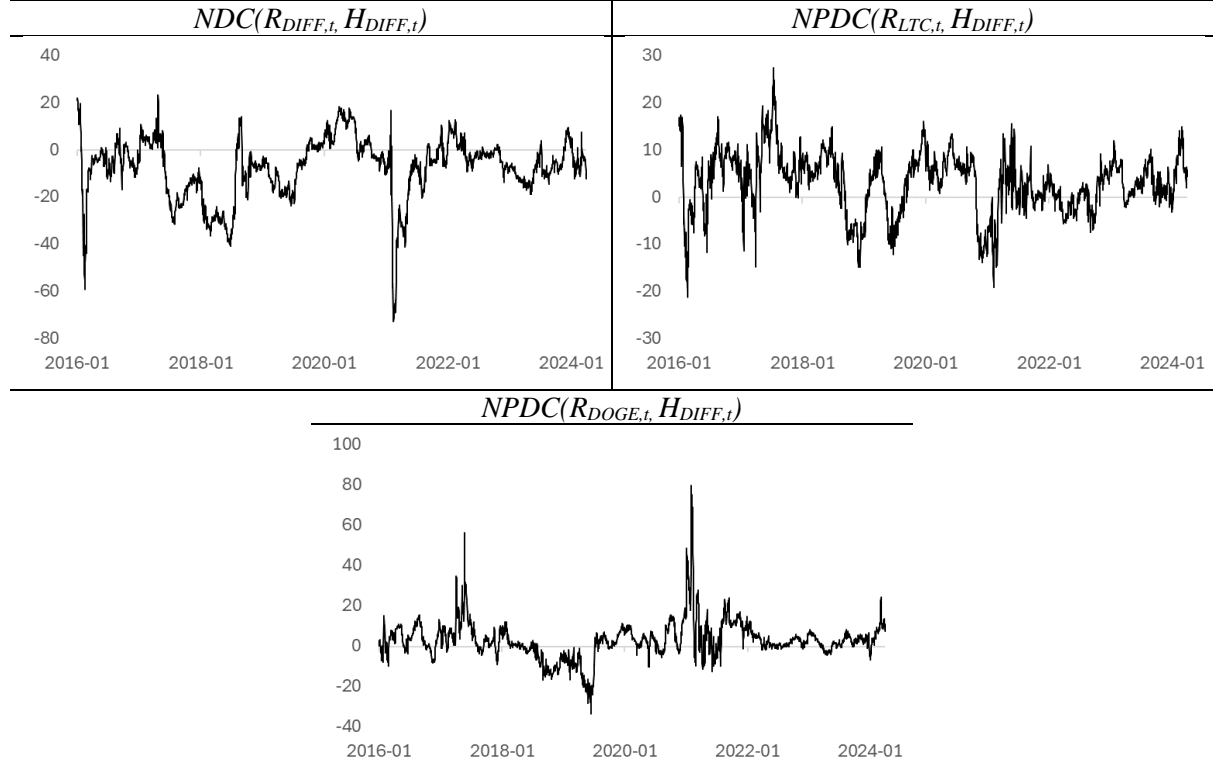


Figure 5. Slope and curvature of NDC and NPDC with respect to quantile

Note. This figure illustrates the time-series dynamics of the slope and curvature coefficient estimates of NDC and NPDC with respect to quantile, which are estimated with two OLS models regressions on a daily basis: $(NDC) \text{ or } (NPDC) = \alpha + \beta \cdot (Quantile) + \varepsilon$ and $(NPDC) = \alpha + \beta_0 \cdot (Quantile) + \beta_1 \cdot (Quantile)^2 + \varepsilon$. For the first and second models, we plot the coefficient estimate for β and β_1 , respectively.

Panel A. Slope coefficient β for $(NDC) \text{ or } (NPDC) = \alpha + \beta \cdot (Quantile) + \varepsilon$



Panel B. Curvature coefficient β_1 for $(NPDC) = \alpha + \beta_0 \cdot (Quantile) + \beta_1 \cdot (Quantile)^2 + \varepsilon$

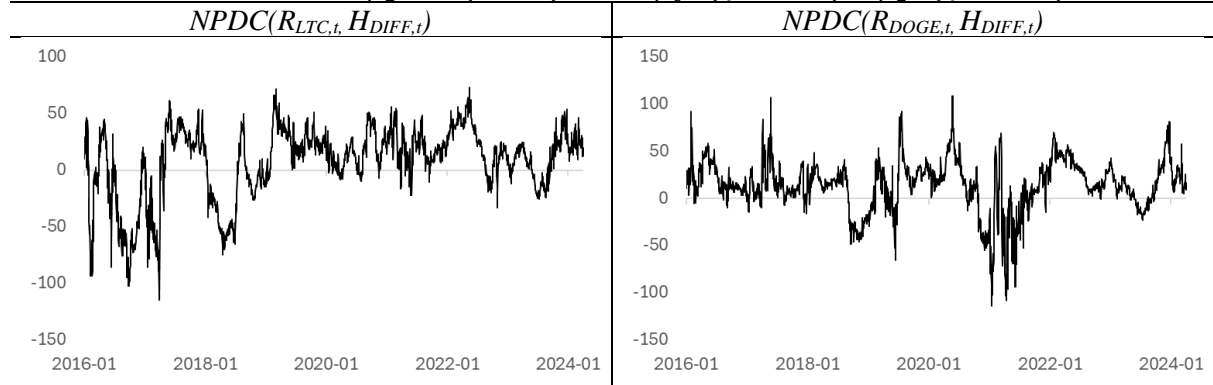


Table 1. Summary statistics

Note. This table presents summary statistics of the 30-day hashrate log growth rates, H , and 30-day log returns, R , for two cryptocurrencies, Litecoin (LTC) and Dogecoin (DOGE), covering a 111-month period from January 2015 to March 2024.

	30-day hashrate log growth rate H			30-day log return R		
	$H_{LTC,t}$	$H_{DOGE,t}$	$H_{DIFF,t}$	$R_{LTC,t}$	$R_{DOGE,t}$	$R_{DIFF,t}$
Mean	0.06	0.06	0.00	0.03	0.06	-0.03
Median	0.05	0.05	0.00	0.01	-0.01	0.00
Maximum	1.29	1.04	0.36	1.60	2.40	1.14
Minimum	-0.79	-0.63	-0.41	-0.90	-1.51	-2.31
Std. dev.	0.20	0.19	0.07	0.30	0.41	0.33
Skewness	1.04	0.80	0.18	0.90	1.95	-1.97
Kurtosis	5.57	3.93	1.65	3.36	6.40	8.25
# of obs.	3,378	3,378	3,378	3,378	3,378	3,378

Table 2. Correlation matrix

Note. This table presents a correlation matrix of the variables employed in our study.

		30-day hashrate log growth rate			30-day log return		
		$H_{LTC,t}$	$H_{DOGE,t}$	$H_{DIFF,t}$	$R_{LTC,t}$	$R_{DOGE,t}$	$R_{DIFF,t}$
30-day hashrate log growth rate	$H_{LTC,t}$	1.000					
	$H_{DOGE,t}$	0.927	1.000				
	$H_{DIFF,t}$	0.306	-0.072	1.000			
30-day log return	$R_{LTC,t}$	0.469	0.437	0.139	1.000		
	$R_{DOGE,t}$	0.287	0.290	0.026	0.605	1.000	
	$R_{DIFF,t}$	0.067	0.034	0.092	0.151	-0.696	1.000

Table 3. Relationship between net directional connectedness and relevant variables

Note. This table reports the regression result of the net directional connectedness indices between $H_{DIFF,t}$ and $R_{DIFF,t}$ on $H_{PC,t}$, $R_{LTC,t}$, and $R_{DOGE,t}$ for the 5th, 50th, and 95th percentiles, where $H_{PC,t}$ is the first principal component of $H_{LTC,t}$ and $H_{DOGE,t}$. The Huber-White sandwich estimator is employed to estimate standard errors and, therefore, unadjusted R^2 is reported. There are 3,180 observations in the sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	5th percentile	50th percentile	95th percentile
$H_{PC,t}$	0.295 (1.36)	-0.019 (-0.31)	0.094 (0.55)
$R_{LTC,t}$	-4.335*** (-3.41)	-1.848*** (-5.21)	3.536*** (3.42)
$R_{DOGE,t}$	4.906*** (4.31)	2.273*** (6.66)	-7.269*** (-8.38)
Constant	11.331*** (46.35)	1.519*** (26.93)	-2.180*** (-11.85)
R^2	0.015	0.048	0.053

Table 4. Relationship between net directional connectedness and dummy variables

Note. This table reports the regression result of the net directional connectedness indices between $H_{DIFF,t}$ and $R_{DIFF,t}$ on dummy variables regarding $H_{PC,t}$, $R_{LTC,t}$ and $R_{DOGE,t}$ for the 50th percentile, where $H_{PC,t}$ is the first principal component of $H_{LTC,t}$ and $H_{DOGE,t}$. 5 (95) in subscripts indicate that the dummy variable have the value of one if the value of the relevant variable is equal to the 5th percentile or less (95th percentile or more). Only the dummy variables are included as independent variables in Column (1), and $H_{PC,t}$, $R_{LTC,t}$, and $R_{DOGE,t}$ are additionally controlled for in Column (2). The Huber-White sandwich estimator is employed to estimate standard errors and, therefore, unadjusted R^2 is reported. There are 3,180 observations in the sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
$H_{PC5,t}$	0.133 (0.41)	-0.014 (-0.04)
$H_{PC95,t}$	0.008 (0.02)	0.051 (0.14)
$R_{LTC5,t}$	-0.122 (-0.46)	-0.828** (-2.59)
$R_{DOGE5,t}$	0.722** (2.58)	1.215*** (3.65)
$R_{LTC95,t}$	-0.368 (-0.95)	0.835* (1.91)
$R_{DOGE95,t}$	3.783*** (6.45)	2.210*** (3.24)
$H_{PC,t}$		-0.038 (-0.52)
$R_{LTC,t}$		-2.111*** (-5.14)
$R_{DOGE,t}$		1.487*** (3.73)
Constant	1.400*** (22.25)	1.402*** (22.50)
R^2	0.054	0.068

Table 5. Relationship between net partial directional connectedness and relevant variables

Note. This table reports the regression result of the net pairwise directional connectedness (NPDC) between $H_{DIFF,t}$ and either $R_{LTC,t}$ or $R_{DOGE,t}$ on $H_{PC,t}$, $R_{LTC,t}$, and $R_{DOGE,t}$ for the 5th, 50th, and 95th percentiles, where $H_{PC,t}$ is the first principal component of $H_{LTC,t}$ and $H_{DOGE,t}$. The Huber-White sandwich estimator is employed to estimate standard errors and, therefore, unadjusted R^2 is reported. There are 3,180 observations in the sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	NPDC between R_{LTC} and H_{DIFF}			NPDC between R_{DOGE} and H_{DIFF}		
	5 th percentile	50 th percentile	95 th percentile	5 th percentile	50 th percentile	95 th percentile
$H_{PC,t}$	-0.104 (-1.54)	0.747*** (9.15)	1.220*** (10.77)	-0.080 (-1.08)	-0.232*** (-4.89)	0.050 (0.34)
$R_{LTC,t}$	-2.607*** (-5.96)	-2.951*** (-6.36)	3.521*** (4.74)	-1.239*** (-2.91)	-1.050*** (-2.79)	-1.771 (-1.47)
$R_{DOGE,t}$	0.266 (0.96)	-1.686*** (-6.17)	-1.985*** (-3.69)	-2.010*** (-8.61)	2.738*** (8.09)	7.050*** (8.01)
Constant	2.800*** (33.27)	2.614*** (24.56)	2.614*** (20.13)	1.656*** (17.63)	0.269*** (4.59)	3.229*** (16.42)
R^2	0.027	0.051	0.072	0.046	0.065	0.052

Table 6. Relationship between net pairwise directional connectedness and dummy variables

Note. This table reports the regression result of the net directional connectedness indices between $H_{DIFF,t}$ and either $R_{LTC,t}$ or $R_{DOGE,t}$ on dummy variables regarding $H_{PC,t}$, $R_{LTC,t}$ and $R_{DOGE,t}$ for the 50th percentile, where $H_{PC,t}$ is the first principal component of $H_{LTC,t}$ and $H_{DOGE,t}$. 5 (95) in subscripts indicate that the dummy variable have the value of one if the value of the relevant variable is equal to the 5th percentile or less (95th percentile or more). Only the dummy variables are included as independent variables in Columns (1) and (3), and $H_{PC,t}$, $R_{LTC,t}$, and $R_{DOGE,t}$ are additionally controlled for in Columns (2) and (4). The Huber-White sandwich estimator is employed to estimate standard errors and, therefore, unadjusted R^2 is reported. There are 3,180 observations in the sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	NPDC between R_{LTC} and H_{DIFF}		NPDC between R_{DOGE} and H_{DIFF}	
	(1)	(2)	(3)	(4)
$H_{PC5,t}$	-3.064*** (-11.12)	-1.026** (-2.12)	1.444*** (7.59)	1.225*** (4.31)
$H_{PC95,t}$	1.055** (2.30)	-1.222* (-1.83)	-3.300*** (-6.43)	-2.917*** (-5.55)
$R_{LTC5,t}$	1.770*** (3.30)	0.201 (0.36)	0.149 (0.87)	0.011 (0.05)
$R_{DOGE5,t}$	0.589 (1.04)	-0.718 (-1.28)	0.525*** (2.97)	0.856*** (3.27)
$R_{LTC95,t}$	-0.905** (-2.15)	1.100** (2.02)	1.591** (2.54)	1.846*** (2.67)
$R_{DOGE95,t}$	-3.485*** (-8.15)	-2.143*** (-3.24)	5.726*** (8.16)	4.845*** (4.53)
$H_{PC,t}$		0.818*** (5.71)		-0.074 (-0.97)
$R_{LTC,t}$		-3.589*** (-6.21)		-0.595 (-1.39)
$R_{DOGE,t}$		-0.900** (-2.14)		0.765 (1.48)
Constant	2.627*** (22.03)	2.774*** (22.98)	0.101 (1.55)	0.085 (1.34)
R^2	0.033	0.059	0.118	0.120

Table 7. Net directional connectedness and dummy variables: Subperiod analysis

Note. This table reports the regression result of the net directional connectedness indices between $H_{DIFF,t}$ and $R_{DIFF,t}$ on dummy variables regarding $H_{PC,t}$, $R_{LTC,t}$ and $R_{DOGE,t}$ for the 50th percentile, where $H_{PC,t}$ is the first principal component of $H_{LTC,t}$ and $H_{DOGE,t}$, for three subperiods. We define subperiods based on the point of structural break for the amount of daily LTC- and DOGE-related tweets. We assume that there is one structural break point for each cryptocurrency, so that there are two points in total. The three subperiods are defined as [January 18, 2015 to June 1, 2017], [June 2, 2017 to January 26, 2021], and [January 27, 2021 to March 31, 2024], respectively. 5 (95) in subscripts indicate that the dummy variable have the value of one if the value of the relevant variable is equal to the 5th percentile or less (95th percentile or more). $H_{PC,t}$, $R_{LTC,t}$, and $R_{DOGE,t}$ are also included as independent variables. The Huber-White sandwich estimator is employed to estimate standard errors and, therefore, unadjusted R^2 is reported. There are 3,180 observations in the sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Subperiod #1	Subperiod #2	Subperiod #3
$H_{PC5,t}$	0.663 (0.80)	-0.261 (-0.54)	-0.045 (-0.12)
$H_{PC95,t}$	-0.539 (-0.66)	-0.344 (-0.65)	0.440 (0.96)
$R_{LTC5,t}$	1.084 (1.48)	-3.135*** (-7.38)	0.260 (1.02)
$R_{DOGE5,t}$	1.722** (2.46)	1.582*** (3.22)	-0.454* (-1.94)
$R_{LTC95,t}$	-1.417 (-1.51)	0.875 (1.14)	-1.886*** (-3.27)
$R_{DOGE95,t}$	-2.054*** (-2.70)	1.581 (1.53)	3.726*** (2.46)
$H_{PC,t}$	0.066 (0.45)	-0.046 (-0.40)	-0.082 (-0.78)
$R_{LTC,t}$	3.029*** (2.85)	-3.769*** (-8.63)	-1.135 (-1.44)
$R_{DOGE,t}$	2.174** (2.13)	2.183*** (3.87)	1.220 (1.51)
Constant	-0.640*** (-4.34)	2.834*** (25.76)	1.120*** (21.14)
# of observations	685	1,335	1,160
R^2	0.076	0.087	0.228

Table 8. *t*-test for the slope and curvature of NDC and NPDC with respect to quantile

Note. This table reports the result of the *t*-tests for the slope and curvature coefficient estimate of NDC and NPDC with respect to quantile, which are estimated with two OLS models regressions on a daily basis: $(NDC) = \alpha + \beta \cdot (Quantile) + \varepsilon$ and $(NPDC) = \alpha + \beta_0 \cdot (Quantile) + \beta_1 \cdot (Quantile)^2 + \varepsilon$. For the first and second models, we conduct a *t*-test on β and β_1 , respectively, to determine whether the daily coefficient estimates are statistically different from zero. We conduct *t*-tests for the entire period as well as subperiods, which are defined based on the point of structural break for the amount of daily LTC- and DOGE-related tweets. We assume that there is one structural break point for each cryptocurrency, so that there are two points in total. The three subperiods are defined as [January 18, 2015 to June 1, 2017], [June 2, 2017 to January 26, 2021], and [January 27, 2021 to March 31, 2024], respectively. The Huber-White sandwich estimator is employed to estimate standard errors and, therefore, unadjusted R^2 is reported. There are 3,180 observations in the sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Slope coefficient β for (NDC) or $(NPDC) = \alpha + \beta \cdot (Quantile) + \varepsilon$

	Entire period	Subperiod #1	Subperiod #2	Subperiod #3
$NDC(R_{DIFF,t}, H_{DIFF,t})$	-6.098*** (-24.907)	1.856*** (3.602)	-9.041*** (-24.069)	-7.409*** (-20.628)
$NPDC(R_{LTC,t}, H_{DIFF,t})$	3.314*** (28.969)	5.061*** (19.348)	3.620*** (18.148)	1.929*** (14.172)
$NPDC(R_{DOGE,t}, H_{DIFF,t})$	2.860*** (17.437)	4.440*** (15.294)	0.206 (0.782)	4.980*** (19.037)
# of observations	3,180	685	1,335	1,160

Panel B. Curvature coefficient β_1 for $(NPDC) = \alpha + \beta_0 \cdot (Quantile) + \beta_1 \cdot (Quantile)^2 + \varepsilon$

	Entire period	Subperiod #1	Subperiod #2	Subperiod #3
$NPDC(R_{LTC,t}, H_{DIFF,t})$	7.071*** (12.910)	-18.725*** (-12.914)	11.037*** (14.518)	17.739*** (14.172)
$NPDC(R_{DOGE,t}, H_{DIFF,t})$	13.507*** (27.885)	18.162*** (25.863)	10.774*** (13.571)	13.903*** (16.175)
# of observations	3,180	685	1,335	1,160