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 fluctuations in prices so that 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, while only the latter being 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. This 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

The majority of classical finance literature in the field of 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 in the market 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 cost advantage. These findings suggest that most cryptocurrency miners retain their competitiveness by investing significant resources to leverage their extensive expertise and informational advantage in the market they are going to participate in, similar to institutional investors. Given this similarity, it is reasonable to expect that miners' investment decisions are also comparable to those of institutional investors and, therefore, less prone to irrational trading motivations compared to non-mining cryptocurrency market traders. This expectation carries more conviction with the findings that the institutional investors in conventional markets rarely trade cryptocurrencies (Chen, Lepori, Tai, and Sung, 2022). However, since the cryptocurrency market is more significantly influenced by irrational factors than conventional markets, it remains uncertain whether the miners' decision-making processes are as unaffected by irrationality as those of institutional investors in other markets. Aysan, Caporin, and Cepni (2024) find that the cryptocurrency market has a higher proportion of retail or less professional investors, making it more susceptible to sentiment fluctuations. Similarly, Gemayel and Preda (2024) argue that the market is dominated by retail investors whose trading activities are driven by market sentiment, fads, informational cascades, and positive feedback trading.

The prevailing influence of irrational factors in the cryptocurrency market can affect the miners' decision-making process in two ways. First, the increased uncertainty due to irrationality may limit the price-stabilizing ability of informed traders, depriving the private information that miners have of its informational value. Stein (1987) theoretically predicts that when more speculative traders are introduced into a market, price destabilization would 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 information asymmetry as fully as institutional investors do in conventional markets.

Second, given the limited informational value of private information, miners may rely more on price as a source of information, especially given the presence of extensive information networks. Ozsoylev and Walden (2011) demonstrate that market participants rely more on price as a source of information when they are more closely interconnected through information networks, which help the participants disentangle noise from price as a public signal. Given the characteristics of the cryptocurrency market, which is significantly affected by information networks such as social media (Guégan and Renault, 2021; Lee and Jeong, 2023), and the structure of the cryptocurrency mining industry, which heavily relies on human networks such as mining pool participants (Arnosti and Weinberg, 2022; Cong, He, and Li, 2021), it is reasonable to expect that miners regard price as a signal more than institutional investors in more siloed markets do, particularly with the lower informational value of private information in the cryptocurrency market.

If miners rely on cryptocurrency prices as a source of information, they will make mining decisions as if they are herding. Namely, if the price of a cryptocurrency surges (drops), miners will devote more (less) mining resources to the cryptocurrency. They can also sell off their inventories following price drops. This behavior is consistent with the concept of herding, which refers to investors' tendency to set aside their own convictions and instead follow the prevailing market consensus. With this herding behavior, the miners' investment decisions would be at least partially affected by the irrational drivers of cryptocurrency prices. This would cause them to act as if they are accepting the irrationality in the market, regardless of whether the miners themselves are indeed irrational. Thus, if we can successfully identify which irrational trading motives prevail in the cryptocurrency market and empirically verify that miners are making investment decisions by following price dynamics, we may conjecture that the prevailing irrational driver in the cryptocurrency market affect not only the non-mining traders but also the miners, with price serving as a conduit.

Among various factors contributing to investor herding, the fear of missing out (FOMO) is commonly cited as a primary reason for herding in the cryptocurrency market (Baur and Dimpfl, 2018; Bleher and Dimpfl, 2019; Kakinaka and Umeno, 2022; Kristoufek, 2020; Kulbhaskar and Subramaniam, 2023). Kuchler and Stroebel (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, biased towards positive news or returns. Saggu (2022) empirically demonstrates that the price reaction to social media in the cryptocurrency market is primarily driven by FOMO, revealing an asymmetric pattern in bitcoin price response, which significantly reacts only to positive news. Hence, if we can reveal that miners react to cryptocurrency price dynamics in an asymmetric way, 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.

The asymmetric pattern in miners' response to price dynamics, if it exists, can be highlighted by the fact that miners are not likely to be major buyers but are major sellers in the cryptocurrency market. Since miners participate in the market mostly 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, there would exist a significantly asymmetric lead-lag relationship between cryptocurrency returns and mining investment decisions that switch directions following the direction of price movement.

Given these hypotheses, it would be meaningful to investigate how mining decisions are related to cryptocurrency returns. However, this investigation is not easily achievable due to the unique way miners engage in the cryptocurrency market. As stated above, 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 to investigate mining decisions. However, mining-related variables are difficult to analyze due to their susceptibility to various factors, for instance, 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 in which 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 allows miners to switch between mining LTC and DOGE, or even mine both simultaneously, without any significant additional hardware investment or re-optimization. This versatility can be demonstrated by mining techniques such as LTC-DOGE merged mining, enabling miners to mine both cryptocurrencies simultaneously without additional computational effort. 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. This relationship is highlighted when DOGE is paired with LTC, which, in contrast, is far from the concept of a memecoin, with the Litecoin blockchain being developed as a sidechain of the Bitcoin blockchain.

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 hashrate growth rate exceptionally significantly when DOGE returns are at their peaks. In contrast, the hashrates does not react in the same way to LTC returns, suggesting that not every cryptocurrency induces a FOMO effect. Furthermore, significantly negative LTC returns tend to follow changes in hashrate growth rate, which implies that miners can also affect cryptocurrency returns from the sell side.

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:

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

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

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

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

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:

$$H_{DIFF,t} = H_{LTC,t} - H_{DOGE,t}, \tag{5}$$

$$R_{DIFF,t} = R_{LTC,t} - R_{DOGE,t}. \tag{6}$$

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 Yılmaz (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 of Gabauer (2022). The following VAR model is adopted to explain $H_{DIFF,t}$ and $R_{DIFF,t}$ in Equations (5) and (6) as an autoregressive function:

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

where $\boldsymbol{y}_t = [H_{DIFF,t} \;\; R_{DIFF,t}]'$ 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, $\boldsymbol{v}_t$ 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:

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

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 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:

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

where $\boldsymbol{e}_i$ 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:

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

so that the conditions $\sum_{i=1}^{2} \widetilde{\Psi}_{ij(\tau)}(H) = 1$ and $\sum_{j=1}^{2} \sum_{i=1}^{2} \widetilde{\Psi}_{ij(\tau)}(H) = 2$ 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:

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

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

To empirically investigate the relationship between LTC-DOGE hashrates and returns, we first estimate the NDC indices 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 index 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 fluctuations in returns.

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 the NDC index indicate that the relative degree of influence between returns and hashrates is time-varying and depends on quantile selection. Second, despite the unclear tendency, the NDC index 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, the NDC index value 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, the NDC index value is often negative, implying that high LTC returns are frequently preceded by significant changes in hashrates.

[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 in more detail the factors determining the relationship between returns and mining decisions. We estimate a set of OLS models using NDC as the dependent variable and the relevant individual factors as independent variables. Given our interest in whether abrupt fluctuations in these factors affect the relationship, we use the absolute returns and absolute hashrate growth rates of each cryptocurrency as independent variables. It should be noted that we can still infer the sign of returns when we examine the top and bottom Q-VAR quantiles. The lower the percentile, the higher the 30-day DOGE log returns compared to the 30-day LTC log returns.

Table 3 presents the regression results. The results highlight three notable characteristics. First, returns tend to influence hashrates more significantly than vice versa when returns are significantly positive, whereas hashrates affect returns more when returns are significantly negative. This tendency implies that cryptocurrency price surges may affect miners' decisions, possibly due to the FOMO effect, but price drops can actually be the consequence of miner's choices, affecting the sell side. Second, the effect of cryptocurrency return volatility on NDC is higher when DOGE returns are significantly higher than LTC returns. Both the coefficient estimates and *t*-statistics are larger for the 5th percentile compared to the 95th percentile. This tendency suggests that the FOMO effect is stronger in the DOGE market while the influence of miners' decisions is more pronounced in the LTC market. Third, abrupt changes in LTC hashrates are closely related to NDC. The changes are associated with greater influence of miners' decisions when LTC returns are relatively low, and with greater influence of cryptocurrency returns when LTC returns are relatively high. This pattern is again consistent with the argument that significantly positive cryptocurrency returns affects miners' decisions, but excessively low cryptocurrency returns are preceded by miners' choices.

[Table 3 about here]

To verify that the empirical results are not attributable to a specific estimation methodology, we finally conduct another set of OLS estimations while controlling for quantiles with a different approach. Instead of conducting OLS estimations for the 5th and 95th Q-VAR percentiles, we employ 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 hashrate growth rates, $H_{LTC5,t}$, $H_{LTC95,t}$, $H_{DOGE5,t}$, and $H_{DOGE95,t}$ in a similar way to control for abrupt fluctuations in hashrate growth rates. As in Section 4.2, we also consider the absolute returns and absolute hashrate growth rates of each cryptocurrency as independent variables to control for both the linear relationship and the additional effect of significantly large fluctuations.

Table 4 presents the regression results. The table demonstrates two interesting features. First, the relationship among NDC, hashrates, and return volatility is significantly affected by large increases in LTC hashrate and abrupt DOGE price surges. Even when return volatility is additionally controlled for in Column (2), the coefficient estimates for $H_{LTC95,t}$, $R_{DOGE5,t}$, and $R_{DOGE95,t}$ are found to be significant. Second, among the volatility variables, only the DOGE return volatility, $|R_{DOGE,t}|$ is found to be significantly related to the NDC index, even after controlling for the dummy variables in Column (2). The strong impact of $|R_{DOGE,t}|$ on the NDC index suggests that the DOGE returns are one of the most influential factors that can explain the relationship between LTC-DOGE hashrates and returns, possibly due to the FOMO effect.

[Table 4 about here]

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. Additionally, significantly negative LTC returns tend to follow changes in hashrate growth rates, suggesting that miners can also influence cryptocurrency returns from the sell side.

We propose two potential implications for future research. First, given that the FOMO effect may influence cryptocurrency miners when no additional investment is required, future research could explore how the level of additional investment required changes this influence. If it can be empirically shown that cryptocurrency miners may purchase or replace their hardware, at least to some degree, following significantly high returns, this behavior can serve as clearer evidence that the FOMO effect influences miners. Second, it would be meaningful if future research determines whether the FOMO effect can delay miners' selling activities. Although this study examines the relationship between returns and mining activities, we do not provide evidence that returns also influence the trading activities of miners. Hence, future research could fill this gap by investigating the relationship between returns and miners' sell volume.

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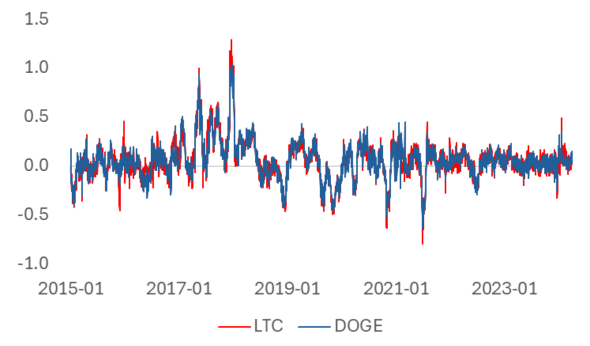
Figure 1. Time-series dynamics of LTC-DOGE hashrate and 30-day returns

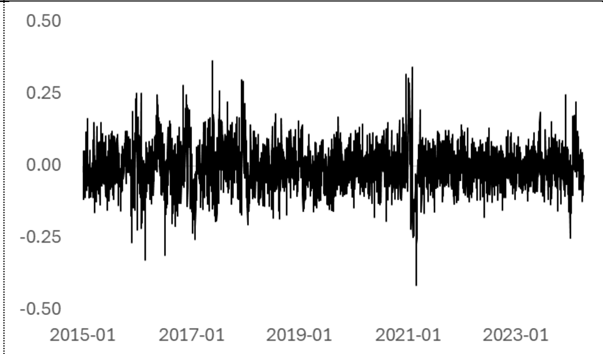
Note. This figure depicts the time-series dynamics of 30-day hashrate log growth rate, *H*, and 30-day returns, *R*, for Litecoin (LTC) and Dogecoin (DOGE), as well as their differences, during the sample period from January 2015 to March 2024. Panel A illustrates the dynamics of the 30-day hashrate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

$H_{LTC,t}$ and $H_{DOGE,t}$

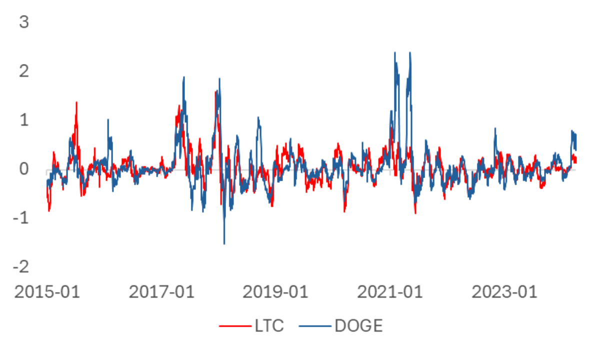


$H_{DIFF,t}$



Panel B. 30-day log-returns *R*

$R_{LTC,t}$ and $R_{DOGE,t}$



$R_{DIFF,t}$

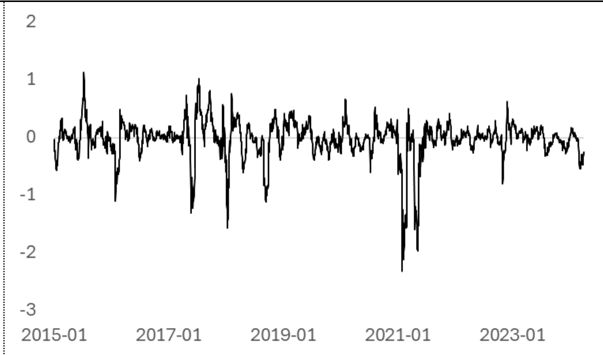
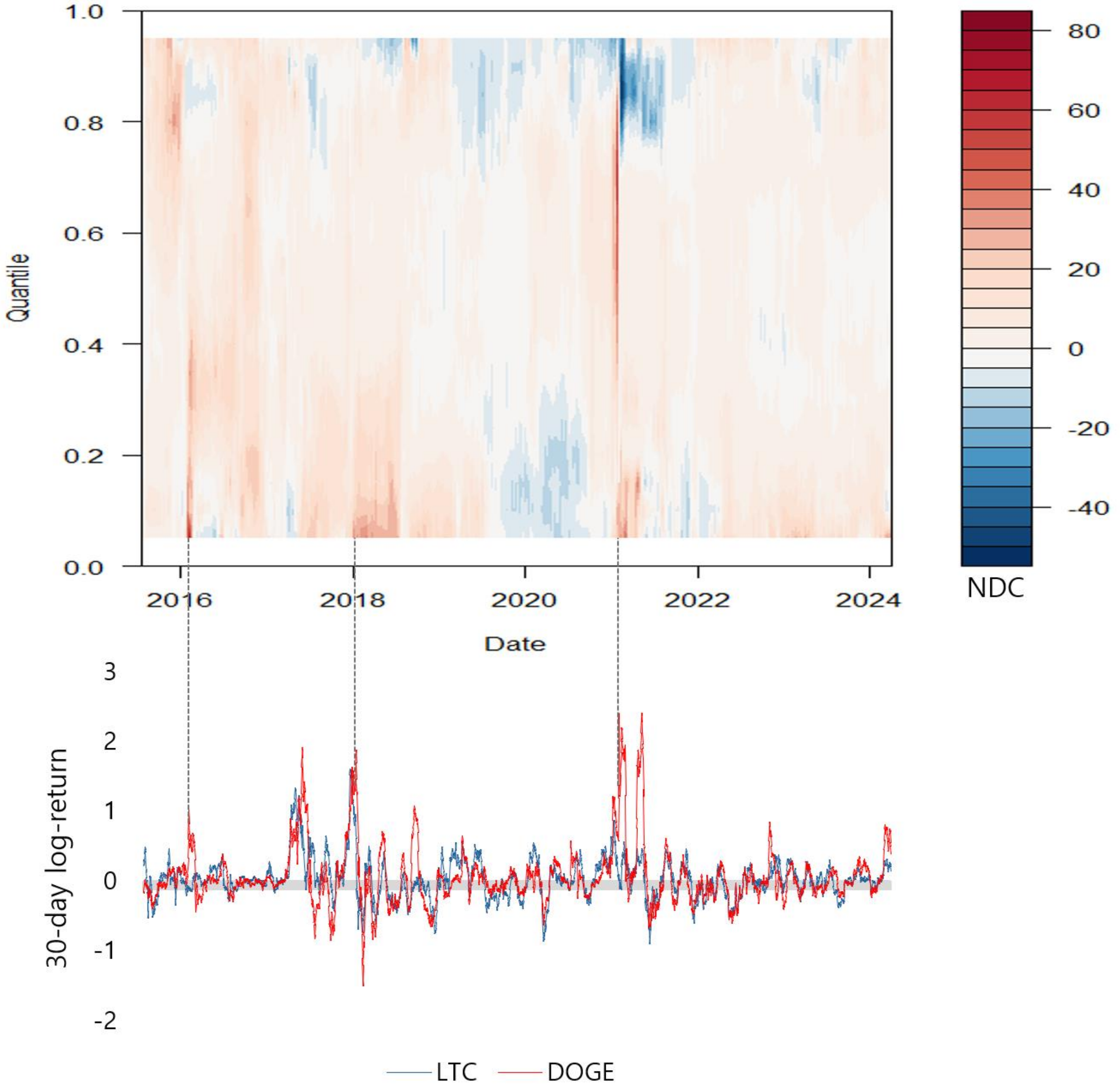


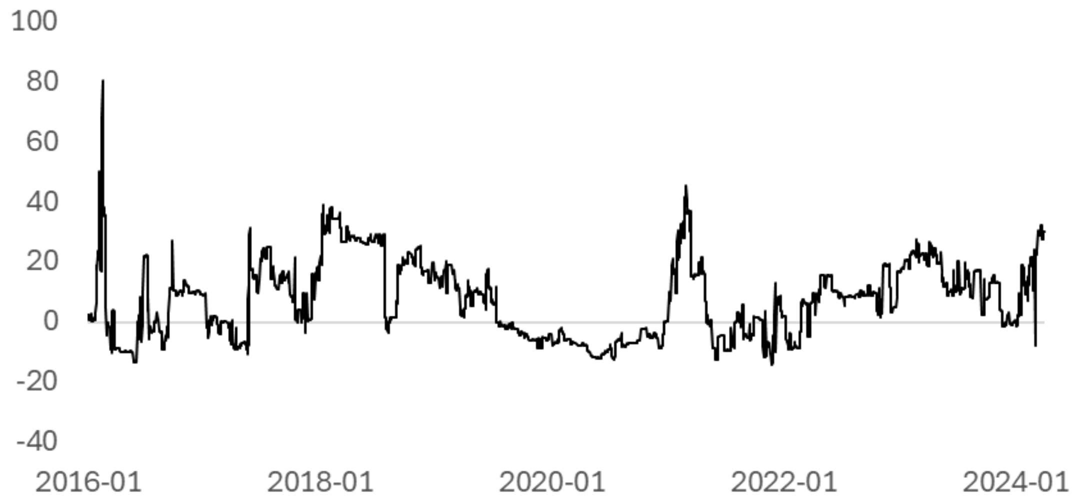
Figure 2. Net directional connectedness between LTC-DOGE hashrate growth and return

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). Positve (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.

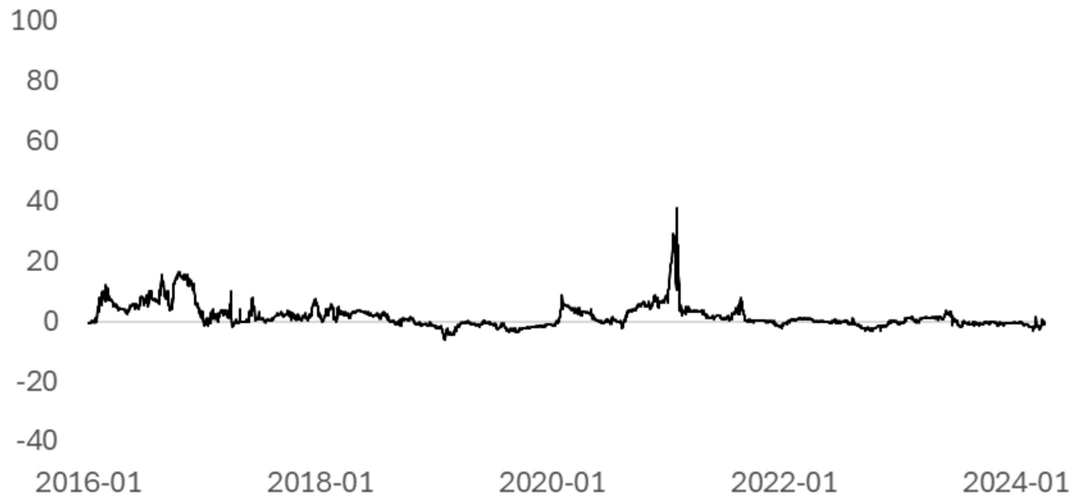
Panel A. All quantiles, matched with 30-day DOGE and LTC returns



Panel B. 5th percentile



Panel C. 50th percentile



Panel D. 95th percentile

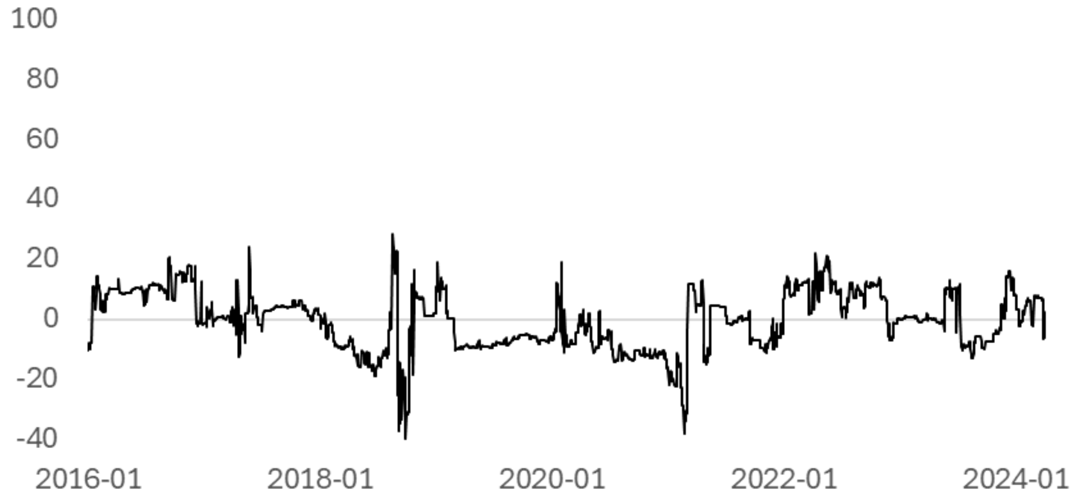


Table 1. Summary statistics

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} and R_{DIFF} on the absolute values of H_{LTC}, H_{DOGE}, R_{LTC}, and R_{DOGE} for the 5th, 50th, and 95th percentiles. 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
$\|H_{LTC,t}\|$	-13.792*	-5.440***	12.294***
	(-1.95)	(-2.81)	(1.97)
$\|H_{DOGE,t}\|$	0.663	2.508	4.740
	(0.08)	(0.90)	(0.72)
$\|R_{LTC,t}\|$	-10.233***	-0.487	3.623***
	(-7.63)	(-1.12)	(2.74)
$\|R_{DOGE,t}\|$	15.114***	2.665***	-6.044***
	(14.24)	(6.75)	(-5.74)
Constant	10.164***	1.128***	-2.353***
	(21.73)	(8.14)	(-5.52)
R^2	0.110	0.063	0.027

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 $H_{LTC,t}$, $H_{DOGE,t}$, $R_{LTC,t}$ and $R_{DOGE,t}$ for the 50th percentile. 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 the absolute values of $H_{LTC,t}$, $H_{DOGE,t}$, $R_{LTC,t}$, 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)
$H_{LTC5,t}$	-0.453	-0.266
	(-1.61)	(-0.77)
$H_{DOGE5,t}$	0.220	-0.058
	(0.66)	(-0.16)
$H_{LTC95,t}$	-0.779**	-0.611*
	(-2.60)	(-1.73)
$H_{DOGE95,t}$	0.248	-0.096
	(0.78)	(0.87)
$R_{LTC5,t}$	-0.119	-0.335
	(-0.45)	(-1.05)
$R_{DOGE5,t}$	0.727**	-0.007
	(2.60)	(-0.02)
$R_{LTC95,t}$	-0.312	-0.653
	(-0.80)	(-1.37)
$R_{DOGE95,t}$	3.795**	1.492*
	(6.51)	(1.89)
$\|H_{LTC,t}\|$		-2.388
		(-0.92)
$\|H_{DOGE,t}\|$		3.691
		(0.95)
$\|R_{LTC,t}\|$		0.138
		(0.26)
$\|R_{DOGE,t}\|$		1.908***
		(3.58)
Constant	1.441**	1.059**
	(22.28)	(5.85)
R^2	0.057	0.068