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Will memecoins' surge trigger a crypto crash? Evidence from the connectedness between leading cryptocurrencies and memecoins

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ABSTRACT

Understanding the crash of cryptocurrencies in 2021 requires analyses of the microstructure of leading cryptocurrencies and memecoins. Using 4-hourly data, we reveal how leading cryptocurrencies and memecoins influence each other with the Granger-causality test and dynamic connectedness. We find that leading cryptocurrencies spillovers dominate memecoins by falling while memecoins spillovers affect leading cryptocurrencies by rising. Moreover, we conduct regression analysis on a daily and 4-hourly basis, and the results confirm the findings above. In most periods, leading cryptocurrencies drive memecoins; however, when memecoins show a positive net spillover, it tends to trigger the leading cryptocurrencies to crash.

1. Introduction

In 2021, the cryptocurrency market fluctuated dramatically and attracted the world's attention. Two leading cryptocurrencies, Bitcoin and Ethereum, reached new all-time highs of $69,000 and $4868, respectively but suffered over a 50% drop. The year saw the emergence of several digital innovations such as DEFI and NFT, and memecoins were one of the most talked about. A memecoin is a cryptocurrency that originated from an Internet meme or has some other humorous characteristic (Nani, 2022; Erdem, 2021). Dogecoin was the first memecoin because it was named after a popular dog on the Internet and got Elon Musk's backing (Shahzad et al., 2022). SHIBA INU's official website refers to Shibcoin as "the end of DOGECOIN", which has quickly gained widespread popularity in the community. Surprisingly, Dogecoin and Shibcoin, two representative memecoins, have skyrocketed by at least 100 times in 2021 and attracted a large number of fresh investors to the cryptocurrency market (Lee et al., 2022; Shahzad et al., 2022).

Interestingly, two big spikes in memecoins preceded the two significant crashes in the cryptocurrency market in 2021. It is natural to ask: will memecoins' surge trigger a crypto crash? Is there any spillover effect between leading cryptocurrencies and memecoins? How do they interact with each other? Has Dogecoin temporarily replaced bitcoin's dominance? Even though the connectedness between cryptocurrencies is not esoteric (Schinckus et al., 2021; Todorovska et al., 2021), surprisingly, there is still a lack of understanding the microstructure of leading cryptocurrencies and memecoins in the cause of risk control and portfolios (Nani, 2022).

Our study fills the gap in two ways. First, we choose 4-hourly price data to capture more accurate and higher frequency information in this year of dramatic fluctuations. Second, we investigate the dynamics return spillovers between leading cryptocurrencies and memecoins, using a dynamic connectedness method based on the time-varying parameter vector autoregressions (TVP-VAR) model.

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Different from the existing literature (Ji et al., 2019; Koutmos, 2018), we analyze the relationship between net total connectedness and price trend of each coin and reveal how the return of one coin affects the net spillover of other coins through dynamic connectedness plots. Furthermore, we establish regression models based on 4-hourly and daily dimensions to verify this analysis.

We also provide an economic explanation for why a spike in memecoins tends to trigger a cryptocurrency market crash. The main results indicate that leading cryptocurrencies are net-transmitters and memecoins are net-receivers in most periods. However, when memecoins showed positive net spillovers, which signaled that the influence of memecoins had risen sharply, and speculative sentiment dominated the market and triggered bubbles, usually followed by a price reversal and market crash (Chen et al., 2019; Renault, 2017).

Our work expands on preceding efforts in cryptocurrencies' literature that analyze dynamic connectedness in cryptocurrency markets (Ji et al., 2019; Koutmos, 2018; Schinckus et al., 2021; Todorovska et al., 2021; Wang et al., 2019). This paper is related to the strand that investigates the sentiment bubbles and co-explosive, the key characteristics of cryptocurrencies (Anamika-Chakraborty and Subramaniam, 2021; Chen et al., 2019; Enoksen et al., 2020; Shahzad et al., 2022). This article has made contributions to the few academic literature on memecoins and social finance (Lee et al., 2022; Erdem, 2021), facilitating future research.

2. Data and methodology

Different from other literature (Akyildirim et al., 2021; Koutmos, 2018), we focus on the relationship between leading cryptocurrencies and memecoins. In this regard, we collect four-hourly closing prices of Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), and Shibcoin (SHIB), which are enough to represent leading cryptocurrencies and memecoins, from Binance and Uniswap. Our sample period is from 9th March to 31st December 2021, dictated by the data availability of Shibcoin. We adjust the timestamp for four cryptocurrencies such that only prices that are available in the same timestamp for four cryptocurrencies are collated to reduce data asymmetry. Finally, we compute cryptocurrency 4-hourly log-return using $ln(P_t/P_{t-1})$.

2.1. *Dynamic connectedness based-on TVP-VAR model*

To evaluate dynamic connectedness measures across leading cryptocurrencies and memecoins, we refer to the variance decomposition methodology outlined in Diebold and Yilmaz (2012) and Antonakakis et al. (2018). The methodology has been widely adopted in literature analyzing directional connectedness and spillover effects between financial markets (Akyildirim et al., 2021; Ji et al., 2019; Koutmos, 2018). We included the details of this method in Appendix A.

2.2. *Linear regression model*

The net total connectedness is the metric we care most about because it reveals the interaction between variables essentially. In this regard, we further develop a linear regression model shown in Eq. (1) to determine whether their daily returns can explain the net return connectedness of each coin *i*.

$$\begin{aligned} NETcoin_i &= c + \beta_1 coin_i\_Returns + \beta_2 Gold + \beta_3 Oil + \beta_4 Msciworld + \beta_5 VIX \\ &+ \beta_6 USEPU + \beta_7 Twitter\_sentiment + \beta_8 Google\_Trends + \varepsilon_i \end{aligned} \tag{1}$$

Referring to the existing literature, we consider the daily price index of spot Gold, WTI Crude Oil (Bouri et al., 2017; Das et al., 2020; Wen et al., 2022), MSCI World Index and CBOE S&P500 implied volatility index (VIX) (Hernandez et al., 2022; Long et al., 2021) as control variables, which is extracted from Datastream. The index of Gold and WTI Crude Oil represent investment-substitution factors that measure the influence of capital inflow and outflow to major commodities (Ji et al., 2019). The MSCI World index denotes global financial factors. We also employ the US Daily Economic Policy Uncertainty Index (USEPU) (Wang et al., 2019) from http://www.policyuncertainty.com/us_monthly.html. It acts as an impact factor for uncertainty together with CBOE VIX. Next, we include the Twitter sentiment index to control for the impact of investor sentiment (Naeem et al., 2021), which can be downloaded from http://hedonometer.org/index.html. Finally, we separately select the volume of Google Trends for Bitcoin, Ethereum, Dogecoin, and Shibcoin as a proxy variable for investor attention (Smales, 2022). All variables are first-differenced. To match these daily data, we use the mean of the 4-hourly net return connectedness data excluding non-trading days.

3. Results

3.1. *Summary statistics*

In this subsection, we report the descriptive statistics and correlations for the returns of four cryptocurrencies. Table 1 indicates that SHIB has the highest mean of returns, followed by DOGE. The highest standard deviation is DOGE's, followed by SHIB. BTC and ETH have a negative skewness, while DOGE and SHIB are positive. All cryptocurrencies have excess levels of kurtosis, especially DOGE. The results of ADF test, LB test and JB test mean that all-time series are stationary and do not follow white noise process and normal distribution.

Table 2 shows a significant positive correlation between Bitcoin and Ethereum, as well as Dogecoin and Shibcoin. There barely exists any significant relationship between these two pairs, namely, leading cryptocurrencies and memecoins. Specifically, the correlation coefficients are higher for the pair BTC/ETH (0.841), whereas DOGE/SHIB has lower correlation coefficients (0.081).

Table 1
Descriptive statistics.

	BTC	ETH	DOGE	SHIB
Mean	−7.76E-05	4.30E-04	6.78E-04	4.54E-03
Std. dev	0.018	0.024	0.122	0.091
Min	−0.138	−0.231	−2.333	−1.450
Max	0.116	0.187	2.332	1.393
Skew	−0.402	−0.220	0.322	1.905
Kurtosis	9.741	14.682	321.141	95.247
Ljung-Box	121.201***	158.139***	366.425***	149.000***
Jarque-Bera	2634.131***	8869.865***	8.00E+06***	5.00E+05***
ADF test	−44.271***	−44.271***	−66.854***	−47.071***

Note: ***, ** and *denote the significance level at 1%, 5% and 10%.

3.2. Granger causality between four cryptocurrencies' returns

We conduct the time-domain Granger-causality test (Granger, 1969) and nonlinear Granger-causality test (Diks and Panchenko, 2006), which is complementary to connectedness measure (Diebold and Yilmaz, 2014) and report the results in Table 3. For linear test, there is a bidirectional causality between BTC and ETH. A unidirectional causality runs from BTC to DOGE and SHIB. The same goes for ETH. Finally, interestingly, SHIB Granger-causes DOGE. The nonlinear test reveals that BTC Granger-causes DOGE. ETH Granger-causes DOGE and SHIB. Finally, SHIB is the Granger cause for DOGE. Overall, the results indicate that leading cryptocurrencies change first and then memecoins follow.

3.3. Average and dynamic connectedness measures

Table 4 reports the averaged connectedness measures, namely spillover indices among four cryptocurrencies for a 10-step-ahead forecast. The *i*th entry in the table represents the estimated contribution to the return forecast error variance of cryptocurrency *i* arising from innovations to cryptocurrency *j*. For example, the shocks to BTC returns are responsible for 39.54% of the 10-step-ahead forecast error variance of ETH, while for DOGE and SHIB is 9.8% and 5.63%, respectively. Similarly, the innovations to DOGE returns contribute 1.47% of the 10-step-ahead forecast error variance for BTC, while for ETH and SHIB is 1.88% and 8.43%, respectively. This suggests the spillover index of leading cryptocurrencies to memecoins is greater than that of the latter to the former. One possible explanation is that memecoin holders tend to be a large number of inexperienced investors, prone to herd behavior and more susceptible to the fluctuations of leading cryptocurrencies. As for the net directional connectedness, the largest is from BTC to others (11.98%) and the smallest is from DOGE to others (−14.02%), which once again indicates the dominant position of leading cryptocurrencies over memecoins.

However, the full-sample spillover indices in Table 4, while providing a summary of the "static" return spillover behavior, probably

Table 2
Correlations among four cryptocurrencies.

	BTC	ETH	DOGE	SHIB
BTC	1			
ETH	0.841***	1		
DOGE	0.030	0.043*	1	
SHIB	−0.023	−0.037	0.081***	1

Note: ***, ** and *denote the significance level at 1%, 5% and 10%.

Table 3
Linear and nonlinear Granger causality tests based on the 4-hourly return data.

Pairs	Null hypothesis	Linear test Chi-sq	P_value	Nonlinear test T_stat	P_value
BTC_ETH	BTC does not Granger Cause ETH	2823.2	0.000	1.238	0.108
	ETH does not Granger Cause BTC	15.343	0.018	0.489	0.312
BTC_DOGE	BTC does not Granger Cause DOGE	24.735	0.000	1.856	0.031
	DOGE does not Granger Cause BTC	5.113	0.529	0.230	0.409
BTC_SHIB	BTC does not Granger Cause SHIB	12.830	0.046	1.120	0.131
	SHIB does not Granger Cause BTC	4.710	0.581	0.071	0.472
ETH_DOGE	ETH does not Granger Cause DOGE	22.081	0.001	2.485	0.006
	DOGE does not Granger Cause ETH	5.047	0.538	−0.045	0.518
ETH_SHIB	ETH does not Granger Cause SHIB	13.197	0.040	1.809	0.035
	SHIB does not Granger Cause ETH	4.760	0.575	−0.530	0.702
DOGE_SHIB	DOGE does not Granger Cause SHIB	6.497	0.370	0.355	0.361
	SHIB does not Granger Cause DOGE	24.178	0.000	1.370	0.085

Table 4
Averaged return connectedness.

	BTC	ETH	DOGE	SHIB	Contribution FROM others
BTC	57.01	39.79	1.47	1.73	42.99
ETH	39.54	56.88	1.88	1.70	43.12
DOGE	9.80	9.30	74.21	6.68	25.79
SHIB	5.63	5.14	8.43	80.8	19.20
Contribution TO others	54.97	54.24	11.77	10.11	131.09
Contribution including own	111.98	111.12	85.98	90.92	TCI
NET directional connectedness	11.98	11.12	−14.02	−9.08	32.77

Note: All values are percentages. The number at the bottom right represents the total connectedness of the system. Variance decompositions are based upon a 4 h TVP-VAR of order 5 and a generalized factorization. Its (*i, j*)th value is the computed contribution to the 10-step-ahead return forecast error variance of cryptocurrency *i* coming from shocks to the returns of cryptocurrency *j*. The diagonal elements represent own variance shares, while the off-diagonal elements reveal spillover rates. The sample period is from 9th March to 31st December 2021.

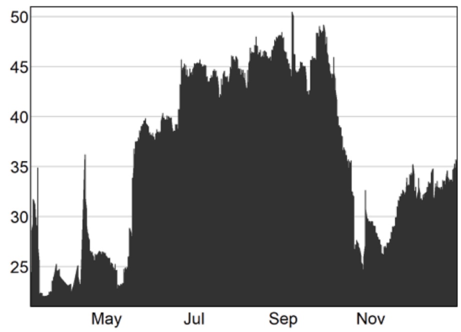

Fig. 1. Dynamic total connectedness of cryptocurrency returns. Notes: Results are based on a TVP-VAR model with lag of order 5 (AIC) and 10-step-ahead generalized forecast error variance decomposition. The sample period is from 9th March to 31st December 2021.

miss some important dynamic details in spillovers. In this regard, we now continue with the dynamic approach to assess the extent and nature of the spillover variation over time.

The total connectedness measures the total spillover or interconnectedness of the network. A low connectedness value shows that most variables are rather independent of each other. Fig. 1 shows that the total connectedness is relatively small in the two periods. The first period is at the beginning of May 2021 because Bitcoin was fluctuating slightly during this period, while the other three cryptocurrencies rose significantly. Especially DOGE and SHIB, the two memecoins, rose more and even once generated the “FOMO” phenomenon. DOGE rose about 130% in just 10 days from April 28 to May 7, while SHIB rose higher, to about 140%. The second period is at the end of October and the beginning of November, during which there was not a significant rise in DOGE, while the other three cryptocurrencies rose sharply.

Fig. 2 presents the spillover from other cryptocurrencies received by BTC and ETH is more stable. Memecoins receive highly variable and increasing spillover from other cryptocurrencies as time advances, indicating their highly volatile and susceptible characteristics to leading cryptocurrencies.

In Fig. 3, we show that the leading cryptocurrencies have relatively higher spillovers to other cryptocurrencies, while the memecoins have relatively lower spillovers to other cryptocurrencies and significantly more extreme pulses, again illustrating their higher volatility and weaker impact on leading cryptocurrencies.

An analysis of Fig. 4 leads to some conclusions. Firstly, regardless of the sign or magnitude of the net total connectedness, BTC and ETH are basically identical, and DOGE and SHIB are consistent. In most periods, the net total connectedness is positive for leading cryptocurrencies and is negative for memecoins, indicating that the leading cryptocurrencies are generally dominant over memecoins. Secondly, the net total connectedness of the leading cryptocurrencies and memecoins is exactly the opposite, denoting that they alternately influence each other. More importantly, the net spillovers of Bitcoin and Ethereum decrease when they go up, and sharply increase when they go down, which suggests their impact on memecoins increases and they play the role of net-transmitter in this period. When memecoins surge, their net spillovers increase significantly to positive, which means they have increased leadership over leading cryptocurrencies, and they are net-transmitters; when memecoins fall, their net spillovers reduce to negative, namely their effects on leading cryptocurrencies decrease, at which time they play the role of net-receivers.

Finally, when the net spillovers of memecoins are positive or increase rapidly from negative and start to show positive, however, the net spillovers of leading cryptocurrencies are exactly the opposite, which means the influence of memecoins spillovers suddenly increases, while the impact of leading cryptocurrencies spillovers suddenly decreases. Note that the surge of memecoins is considered to be representative of speculative sentiment and herd behavior (Enoksen et al., 2020; Erdem, 2021; Lee et al., 2022). At the time, the market is dominated by speculative sentiment and during the post-bubble period, which is normally followed by a price reversal and

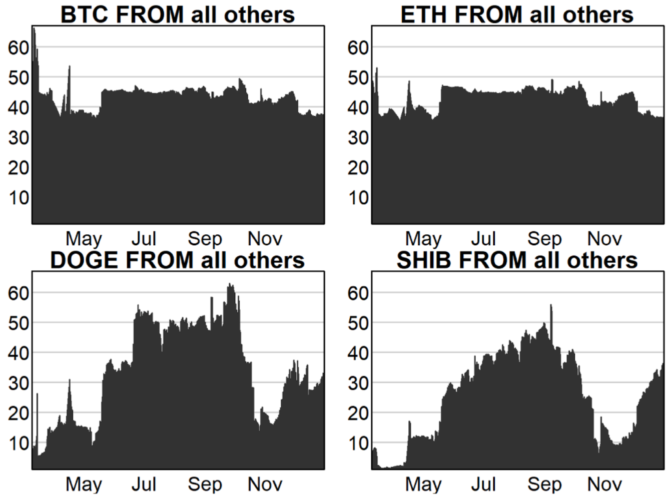

Fig. 2. Directional return spillovers, FROM all others. Notes: Results are based on a TVP-VAR model with lag of order 5 (AIC) and 10-step-ahead generalized forecast error variance decomposition. The sample period is from 9th March to 31st December 2021.

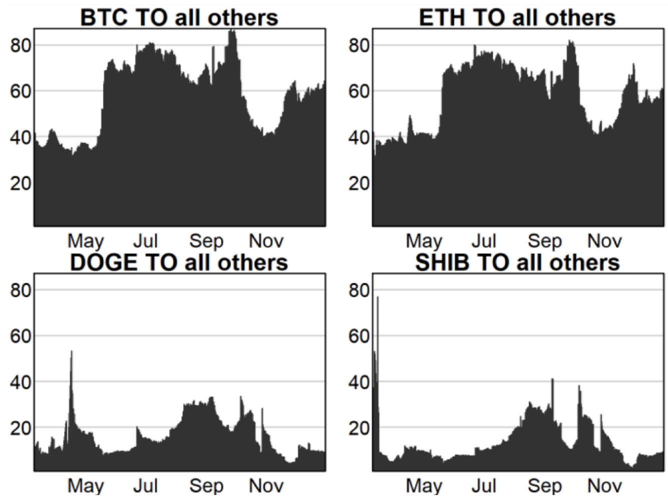

Fig. 3. Directional return spillovers, TO all others. Notes: Results are based on a TVP-VAR model with lag of order 5 (AIC) and 10-step-ahead generalized forecast error variance decomposition. The sample period is from 9th March to 31st December 2021.

may trigger a market-wide crash (Anamika-Chakraborty and Subramaniam, 2021; Bouri et al., 2019; Chen et al., 2019; Renault, 2017; Chuen et al., 2017).

Fig. 5 shows the net pairwise connectedness between BTC and ETH is low. In April and October, memecoins have positive spillovers to leading cryptocurrencies, separately followed closely by a sharp drop in the market, which can also be found in Fig. 4.

3.4. Determinants of net total directional connectedness

We verify the results in Fig. 4 with regression analyses. Table 5 shows that when BTC and ETH rise, their net spillover decrease significantly; in other words, when they fall, their net spillover increase significantly. On the contrary, the net spillovers of DOGE and SHIB increase as they rise, which is in line with Fig. 4. Tables 6 and 7 indicate that the net connectedness of memecoins is negative in the case of leading cryptocurrencies falling, while Tables 8 and 9 illustrate that the net connectedness of leading cryptocurrencies is negative when memecoins surge. In short, the results above suggest that the leading cryptocurrencies dominate memecoins mainly by going down, while memecoins drive the leading cryptocurrencies mainly by going up. One possible explanation is that the decline of leading cryptocurrencies will increase the panic of memecoin investors, leading to their selling behavior; while in the upswing period, memecoins rose more dramatical, thus attracting the funds originally invested in leading cryptocurrencies, making the dominance of the latter weaker.

Moreover, when the prices of leading cryptocurrencies and memecoins changed by the same magnitude, the net spillover of leading

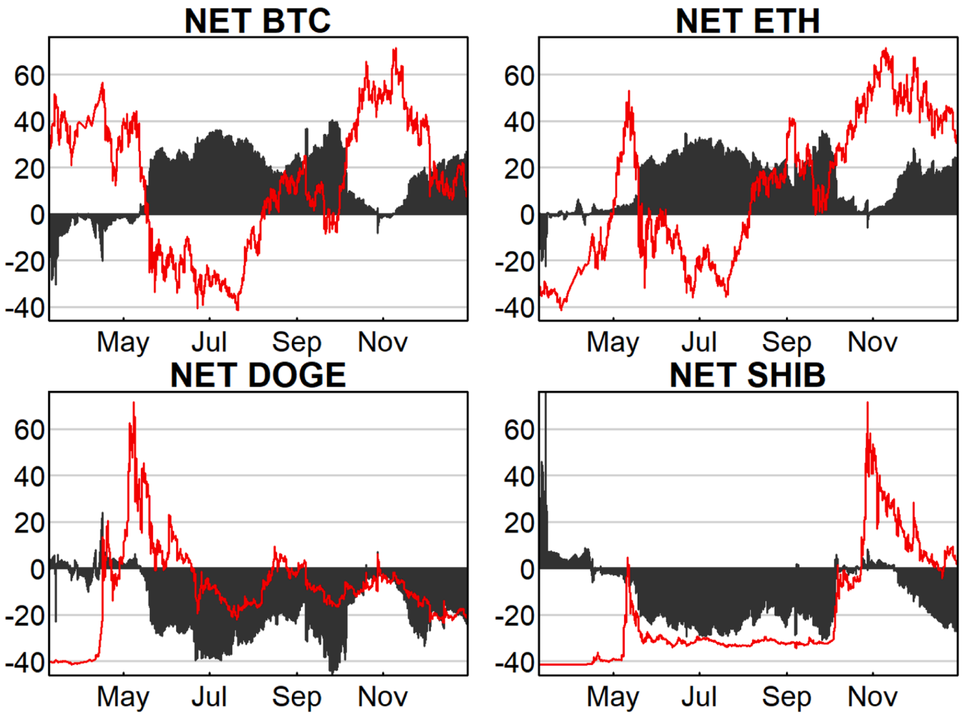

Fig. 4. Net total directional connectedness. Notes: Results are based on a TVP-VAR model with lag of order 5 (AIC) and 10-step-ahead generalized forecast error variance decomposition. The shaded area illustrates the net total spillover of each coin, whereas the solid red line represents the individual coin price. The sample period is from 9th March to 31st December 2021.

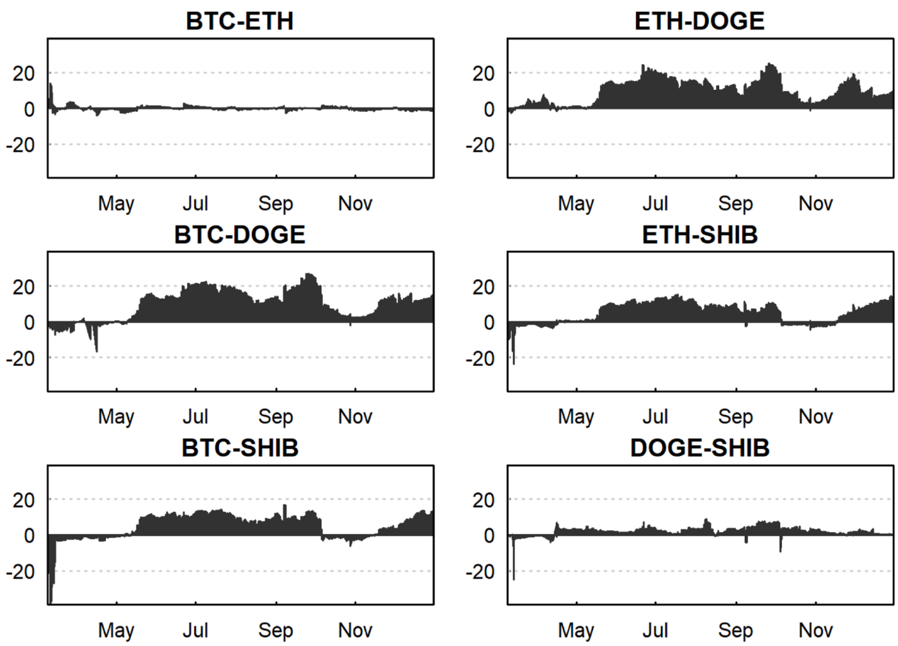

Fig. 5. Net pairwise directional connectedness. Notes: Results are based on a TVP-VAR model with lag of order 5 (AIC) and 10-step-ahead generalized forecast error variance decomposition. The sample period is from 9th March to 31st December 2021.

cryptocurrencies changed by a greater magnitude, indicating their greater driving power over memecoins. Specifically, in terms of magnitude the net connectedness of four cryptocurrencies follow the unique order NETBTC>NETETH>ETDOGE>NETSHIB, which coincides with their market capitalization in order of size.

Table 5
Determinants of net total directional connectedness based on daily data.

	NETBTC	NETETH	NETDOGE	NETSHIB
BTC_Returns	−3.391***			
	(0.932)			
ETH_Returns		−2.220***		
		(0.623)		
DOGE_Returns			1.781***	
			(0.522)	
SHIB_Returns				0.519*
				(0.305)
Gold	−0.003	−0.002	0.002	0.002
	(0.003)	(0.002)	(0.003)	(0.003)
Oil	−0.011	−0.015	−0.039	0.056
	(0.028)	(0.026)	(0.032)	(0.037)
Msciworld	0.004	0.001	0.002	−0.004
	(0.004)	(0.003)	(0.004)	(0.005)
VIX	0.025	0.009	0.038	−0.063
	(0.040)	(0.037)	(0.046)	(0.052)
USEPU	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Twitter_sentiment	−0.967	−0.329	0.157	1.146
	(1.009)	(0.948)	(1.164)	(1.443)
Google_Trends	0.002	−0.001	−0.001	0.002
	(0.004)	(0.003)	(0.003)	(0.003)
Constant	5.846	2.011	−0.967	−6.935
	(6.074)	(5.705)	(7.005)	(8.685)
Adj.R^2	0.048	0.047	0.027	0.013

Note: This table provides estimated coefficients for the model specified in Eq. (1). The dependent variable is the daily net total directional connectedness for Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE) and Shibcoin (SHIB) respectively. The key explanatory variable is the daily return for BTC (BTC_Returns), ETH (ETH_Returns), DOGE (DOGE_Returns) and SHIB (SHIB_Returns). Control variables include the daily index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (EPU), the Twitter sentiment (Twitter_sentiment) and the Google Trends (Google_Trends) for Bitcoin, Ethereum, Dogecoin and Shibcoin, separately. Sample period is March 9th, 2021–December 31st, 2021. Standard errors are given in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%.

Table 6
Determinants of net total directional connectedness based on daily data (BTC_Returns).

	NETBTC	NETETH	NETDOGE	NETSHIB
BTC_Returns	−3.391***	−3.347***	4.180***	2.558**
	(0.932)	(0.863)	(1.063)	(1.184)
Gold	−0.003	−0.003	0.002	0.003
	(0.003)	(0.002)	(0.003)	(0.003)
Oil	−0.011	−0.013	−0.032	0.056
	(0.028)	(0.026)	(0.031)	(0.035)
Msciworld	0.004	0.000	0.001	−0.005
	(0.004)	(0.003)	(0.004)	(0.005)
VIX	0.025	0.002	0.037	−0.064
	(0.040)	(0.037)	(0.045)	(0.050)
USEPU	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Twitter_sentiment	−0.967	0.080	−0.085	0.972
	(1.009)	(0.934)	(1.150)	(1.281)
BTC_Trends	0.002	0.000	−0.000	−0.002
	(0.004)	(0.004)	(0.005)	(0.006)
Constant	5.846	−0.460	0.492	−5.878
	(6.074)	(5.625)	(6.923)	(7.713)
Adj.R^2	0.048	0.061	0.050	0.022

Note: This table provides estimated coefficients for the model specified in Eq. (1). The dependent variable is the daily net total directional connectedness for Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE) and Shibcoin (SHIB) respectively. The key explanatory variable is the daily return for ETH (BTC_Returns). Control variables include the daily index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (EPU), the Twitter sentiment (Twitter_sentiment) and the Google Trends for Bitcoin (BTC_Trends). Sample period is March 9th, 2021-December 31st, 2021. Standard errors are given in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%.

Table 7
Determinants of net total directional connectedness based on daily data (ETH_Returns).

	NETBTC	NETETH	NETDOGE	NETSHIB
ETH_Returns	−2.345***	−2.220***	2.268***	2.297***
	(0.672)	(0.623)	(0.777)	(0.842)
Gold	−0.002	−0.002	0.001	0.002
	(0.003)	(0.002)	(0.003)	(0.003)
Oil	−0.014	−0.015	−0.031	0.060*
	(0.028)	(0.026)	(0.032)	(0.035)
Msciworld	0.004	0.001	0.001	−0.006
	(0.004)	(0.003)	(0.004)	(0.005)
VIX	0.032	0.009	0.027	−0.068
	(0.040)	(0.037)	(0.046)	(0.050)
USEPU	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Twitter_sentiment	−1.460	−0.329	0.295	1.494
	(1.021)	(0.948)	(1.182)	(1.280)
ETH_Trends	−0.001	−0.001	−0.001	0.003
	(0.004)	(0.003)	(0.004)	(0.004)
Constant	8.818	2.011	−1.803	−9.025
	(6.148)	(5.705)	(7.113)	(7.703)
Adj.R^2	0.037	0.047	0.010	0.038

Note: This table provides estimated coefficients for the model specified in Eq. (1). The dependent variable is the daily net total directional connectedness for Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE) and Shibcoin (SHIB) respectively. The key explanatory variable is the daily return for ETH (ETH_Returns). Control variables include the daily index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (EPU), the Twitter sentiment (Twitter_sentiment) and the Google Trends for Ethereum (ETH_Trends). Sample period is March 9th, 2021–December 31st, 2021. Standard errors are given in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%.

Table 8
Determinants of net total directional connectedness based on daily data (DOGE_Returns).

	NETBTC	NETETH	NETDOGE	NETSHIB
DOGE_Returns	−1.325***	−1.507***	1.781***	1.051*
	(0.459)	(0.422)	(0.522)	(0.577)
Gold	−0.002	−0.002	0.002	0.002
	(0.003)	(0.002)	(0.003)	(0.003)
Oil	−0.006	−0.007	−0.039	0.052
	(0.028)	(0.026)	(0.032)	(0.035)
Msciworld	0.003	−0.001	0.002	−0.004
	(0.004)	(0.003)	(0.004)	(0.005)
VIX	0.025	0.000	0.038	−0.063
	(0.040)	(0.037)	(0.046)	(0.051)
USEPU	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Twitter_sentiment	−1.131	−0.105	0.157	1.079
	(1.024)	(0.941)	(1.164)	(1.285)
DOGE_Trends	−0.001	0.001	−0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	6.832	0.658	−0.967	−6.523
	(6.163)	(5.665)	(7.005)	(7.738)
Adj.R^2	0.019	0.047	0.027	0.016

Note: This table provides estimated coefficients for the model specified in Eq. (1). The dependent variable is the daily net total directional connectedness for Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE) and Shibcoin (SHIB) respectively. The key explanatory variable is the daily return for DOGE (DOGE_Returns). Control variables include the daily index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (EPU), the Twitter sentiment (Twitter_sentiment) and the Google Trends for Dogecoin (DOGE_Trends). Sample period is March 9th, 2021–December 31st, 2021. Standard errors are given in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%.

Table 9
Determinants of net total directional connectedness based on daily data (SHIB_Returns).

	NETBTC	NETETH	NETDOGE	NETSHIB
SHIB_Returns	−0.485**	−0.492*	0.467*	0.519*
	(0.238)	(0.256)	(0.274)	(0.305)
Gold	−0.002	−0.002	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Oil	−0.005	−0.010	−0.037	0.056
	(0.028)	(0.027)	(0.033)	(0.037)
Msciworld	0.002	−0.001	0.003	−0.004
	(0.004)	(0.004)	(0.004)	(0.005)
VIX	0.031	0.007	0.027	−0.063
	(0.041)	(0.038)	(0.047)	(0.052)
USEPU	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Twitter_sentiment	−1.086	−0.142	−0.061	1.146
	(1.049)	(1.032)	(1.208)	(1.443)
SHIB_Trends	−0.002	−0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.003)
Constant	6.573	0.890	0.338	−6.935
	(6.317)	(6.214)	(7.275)	(8.685)
Adj.R^2	0.001	0.003	−0.018	0.013

Note: This table provides estimated coefficients for the model specified in Eq. (1). The dependent variable is the daily net total directional connectedness for Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE) and Shibcoin (SHIB) respectively. The key explanatory variable is the daily return for SHIB (SHIB_Returns). Control variables include the daily index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (EPU), the Twitter sentiment (Twitter_sentiment) and the Google Trends for Shibcoin (SHIB_Trends). Sample period is March 9th, 2021–December 31st, 2021. Standard errors are given in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%.

To further investigate the determinants of net total directional connectedness at a higher frequency, we ran regression analyses for each of the four coins during typical periods of rising and falling. Since the cryptocurrency market is traded 7 × 24 h, while the traditional financial market is traded only during specific periods of the trading day, we normalize the raw data using the daily time series to obtain the 4-hourly series in our study. Table B.1 and Table B.2 (see Appendix B) further confirm that net total connectedness is negatively correlated with leading cryptocurrencies' returns in both up and down periods, that is, when they fall, their net spillovers increase. Interestingly, ETH shows stronger spillover effects than BTC when they fall, suggesting its stronger dominance. On the contrary, DOGE and SHIB demonstrate significant positive spillover as they spike in Table B.3 and Table B.4, which means memecoins, especially SHIB have a great impact on leading cryptocurrencies at this time.

4. Conclusion

This paper analyzes the return spillover effects between the two types of coins in the cryptocurrency market in 2021. We further employ the regression model to explain the relationship between cryptocurrencies' returns and their net total connectedness on a daily and 4-hourly basis. We find that the net total spillovers of leading cryptocurrencies increase and that of memecoins decline significantly when the former go down, while the net spillovers of memecoins increase and that of leading cryptocurrencies decrease significantly when the former boom. This suggests that leading cryptocurrencies spillovers dominate memecoins mainly by falling, while memecoins spillovers mostly drive leading cryptocurrencies by rising. The possible reason is that the leading cryptocurrencies' drop led to panic among memecoin investors, prompting them to sell; while during the up period, memecoins rose even more, thus attracting the capital originally invested in leading cryptocurrencies, making the latter less dominant.

In most periods, leading cryptocurrencies are net-transmitters. However, when memecoins start to show positive net spillovers, it indicates an irrational increase in the demand for the speculative asset, and the bubble has reached a severe point, foreshadowing the risk of a market spectacular crash.

This paper enriches the few existing literature on memecoins (Nani, 2022; Erdem, 2021). The findings of this paper present some implications for investors and regulators. Consistent with Tan et al. (2021), investors can manage risk effectively based on this phenomenon illustrated in this paper to promptly identify bubble risk and optimize portfolios. Policymakers can intervene as necessary during periods of market mania to ensure healthy and smooth market operation.

CRediT authorship contribution statement

Chao Li: Data curation, Writing – original draft, Writing – review & editing. **Haijun Yang:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

This paper is no financial interest to report

Data Availability

Data will be made available on request.

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Appendix

A. Dynamic connectedness based-on TVP-VAR model

In this section, we make a brief introduction to the dynamic connectedness measure. According to the Akaike information criterion (AIC) we estimate a TVP-VAR (5) which can be outlined as:

$$z_t = B_t z_{t-1} + u_t \quad u_t \sim N(0, S_t) \tag{A.1}$$

$$vec(B_t) = vec(B_{t-1}) + v_t \quad v_t \sim N(0, R_t) \tag{A.2}$$

where z_t, z_{t-1} and u_t are $N \times 1$ vectors and B_t and S_t are $N \times N$ matrices. $vec(B_t)$ and v_t are $N^2 \times 1$ vectors whereas R_t is a $N^2 \times N^2$ matrix.

Subsequently, we compute the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) and transform the estimated TVP-VAR model into a TVP-VMA process based on the Wold theorem using the following equality: $z_t = \sum_{i=1}^{p} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j}$. Then we normalize the (unscaled) GFEVD $\phi_{ij,t}^{g}(H)$ to the (scaled) GFEVD, $\widetilde{\phi}_{ij,t}^{g}(H)$, in order that each row sums up to unity. Hence, $\widetilde{\phi}_{ij,t}^{g}(H)$, represents the influence variable j has on variable i in terms of its forecast error variance share which is computed by,

$$\phi_{ij,t}^{g}(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(\iota_i' A_t S_t \iota_j\right)^2}{\sum_{j=1}^{N} \sum_{t=1}^{N} \left(\iota_i A_t S_t A_t' \iota_i\right)} \tag{A.3}$$

$$\widetilde{\phi}_{ij,t}^{g}(H) = \frac{\phi_{ij,t}^{g}(H)}{\sum_{j=1}^{N} \phi_{ij,t}^{g}(H)} \tag{A.4}$$

where $\sum_{j=1}^{N} \widetilde{\phi}_{ij,t}^{g}(H) = 1$, $\sum_{i,j=1}^{N} \widetilde{\phi}_{ij,t}^{g}(H) = N$, and ι_i corresponds to a selection vector with unity on the ith position and zero otherwise. Finally, we derive the connectedness measures by the GFEVD as follows:

$$TO_{jt} = \sum_{i=1, i \neq j}^{N} \widetilde{\phi}_{ij,t}^{g}(H) \tag{A.5}$$

$$FROM_{jt} = \sum_{i=1, i \neq j}^{N} \widetilde{\phi}_{ji,t}^{g}(H) \tag{A.6}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{A.7}$$

$$TCL_t = N^{-1} \sum_{j=1}^{N} TO_{jt} \equiv N^{-1} \sum_{j=1}^{N} FROM_{jt} \tag{A.8}$$

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

where $\widetilde{\phi}_{ij,t}^{g}(H)$ illustrates the impact a shock in variable j has on variable i. Eq. (A.5) represents the spillovers of variable j to all others i which is defined as the *total directional connectedness to others* whereas Eq. (A.6) illustrates the spillovers of variable j from all others i that is defined as the *total directional connectedness from others*. Eq. (A.7) calculates the differences between the total directional connectedness to others and total directional connectedness from others to get the *net total directional connectedness* which indicates whether a variable is a net-transmitter or a net-receiver of shocks. Eq. (A.8) is the total connectedness index (TCL_t) indicates the average impact one variable has on all *others*, representing the interconnectedness of the network. Finally, Eq. (A.9) computes the *net pairwise directional connectedness* to examine the bilateral relationship between variable j and i, which exhibits whether variable j is driving variable *i* or vice versa. If $NPDC_{ij,t} > 0(NPDC_{ij,t} < 0)$, it suggests that variable *j* is driving (drived by) variable *i*.

B. Determinants of net total directional connectedness based on 4-hourly data

Table B.1
Determinants of net total directional connectedness for BTC based on 4-hourly data.

	NETBTC (Model 1)	NETBTC (Model 2)
Panel A: Fall		
BTC_Returns	-3.112**	-2.679**
	(1.300)	(1.306)
Gold		0.002
		(0.002)
Oil		0.008
		(0.028)
Msciworld		-0.004
		(0.004)
VIX		-0.044
		(0.042)
USEPU		-0.001
		(0.001)
Twitter_senbtimenbt		-0.127
		(1.319)
BTC_Trenbds		0.006**
		(0.002)
Constant	0.039	0.809
	(0.031)	(7.926)
Panel B: Rise		
BTC_Returns	-14.975**	-12.521**
	(5.091)	(5.199)
Gold		-0.009
		(0.006)
Oil		-0.102
		(0.085)
Msciworld		0.010
		(0.008)
VIX		0.157
		(0.098)
USEPU		0.001
		(0.002)
Twitter_senbtimenbt		-1.990
		(3.738)
BTC_Trenbds		0.008
		(0.015)
Constant	-0.039	12.023
	(0.072)	(22.537)

Note: This table provides estimated coefficienbts for the model specified in Eq.(1). The depenbdenbt variable is the 4-hourly net total directional connectedness for Bitcoin (BTC). The key explanatory variable is the 4-hourly return for BTC (BTC_Returns). Control variables include the 4-hourly index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (EPU), the Twitter senbtimenbt (Twitter_senbtimenbt) and the Google Trenbds for Bitcoin (BTC_Trenbds). Panel A provides estimates of the models for the falling period. Accordingly, Panel B provides estimates of the models for the rising period. Model 1 provides estimates for univariate models of returns of BTC (BTC_Returns) and Model 2 provides estimates for the multiple regression including all variables. Sample period for falling and rising is May 12th, 2021-July 20th, 2021 and August 25th, 2021-October 25th, 2021, respectively. Standard errors are givenb in parenbtheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Table B.2
Determinants of net total directional connectedness for ETH based on 4-hourly data.

	NETETH (Model 1)	NETETH (Model 2)
Panel A: Fall		
ETH_Returns	-3.084***	-3.028***
	(0.858)	(0.870)
Gold		0.003
		(0.002)
Oil		0.008
		(0.026)
Msciworld		-0.004
		(0.004)
VIX		-0.045
		(0.039)
USEPU		-0.001
		(0.001)
Twitter_senbtimenbt		0.584
		(1.201)
ETH_Trenbds		0.003
		(0.003)
Constant	0.022	-3.472
	(0.031)	(7.212)
Panel B: Rise		
ETH_Returns	-10.790***	-8.921**
	(3.868)	(3.973)
Gold		-0.004
		(0.005)
Oil		-0.088
		(0.072)
Msciworld		0.011
		(0.007)
VIX		0.182**
		(0.086)
USEPU		0.000
		(0.002)
Twitter_senbtimenbt		1.643
		(3.241)
ETH_Trenbds		-0.008
		(0.013)
Constant	-0.072	-9.917
	(0.063)	(19.539)

Note: This table provides estimated coefficienbts for the model specified in Eq.(1). The depenbdenbt variable is the 4-hourly net total directional connectedness for Ethereum (ETH). The key explanatory variable is the 4-hourly return for ETH (ETH_Returns). Control variables include the 4-hourly index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (US EPU), the Twitter senbtimenbt (Twitter_senbtimenbt) and the Google Trenbds for Ethereum (ETH_Trenbds). Panel A provides estimates of the models for the falling period. Accordingly, Panel B provides estimates of the models for the rising period. Model 1 provides estimates for univariate models of returns of ETH (ETH_Returns) and Model 2 provides estimates for the multiple regression including all variables. Sample period for falling and rising is May 12th, 2021-July 20th, 2021 and August 25th, 2021-October 25th, 2021, respectively. We truncate ETH_Returns on the high enbd at the 1% level. Standard errors are givenb in parenbtheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Table B.3
Determinants of net total directional connectedness for DOGE based on 4-hourly data.

	NETDOGE (Model 1)	NETDOGE (Model 2)
Panel A: Rise		
DOGE_Returns	1.072***	1.082***
	(0.293)	(0.297)
Gold		-0.001
		(0.009)
Oil		-0.004
		(0.067)
Msciworld		0.004
		(0.009)
VIX		-0.013
		(0.149)
USEPU		0.000
		(0.001)
Twitter_senbtimenbt		-3.287
		(4.427)
DOGE_Trenbds		-0.002
		(0.003)
Constant	-0.010	19.601
	(0.092)	(26.415)
Panel B: Fall		
DOGE_Returns	14.259***	14.394***
	(1.500)	(1.511)
Gold		0.002
		(0.003)
Oil		0.032
		(0.029)
Msciworld		-0.004
		(0.004)
VIX		-0.032
		(0.037)
USEPU		0.000
		(0.000)
Twitter_senbtimenbt		-0.125
		(0.973)
DOGE_Trenbds		-0.003
		(0.008)
Constant	-0.051	0.693
	(0.038)	(5.883)

Note: This table provides estimated coefficienbts for the model specified in Eq.(1). The depenbdenbt variable is the 4-hourly net total directional connectedness for Dogecoin (DOGE). The key explanatory variable is the 4-hourly return for DOGE (DOGE_Returns). Control variables include the 4-hourly index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (US EPU), the Twitter senbtimenbt (Twitter_senbtimenbt) and the Google Trenbds for Dogecoin (DOGE_Trenbds). Panel A provides estimates of the models for the rising period. Accordingly, Panel B provides estimates of the models for the falling period. Model 1 provides estimates for univariate models of returns of DOGE (DOGE_Returns) and Model 2 provides estimates for the multiple regression including all variables. Sample period for rising is March 9th, 2021-May 7th, 2021. And sample period for falling is May 25th, 2021-June 21th, 2021, August 24th, 2021-September 28th, 2021, and October 29th, 2021-December 31st, 2021, respectively. Standard errors are givenb in parenbtheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Table B.4
Determinants of net total directional connectedness for SHIB based on 4-hourly data.

	NETSHIB (Model 1)	NETSHIB (Model 2)
Panel A: Rise		
SHIB_Returns	6.174**	5.281*
	(2.631)	(2.712)
Gold		-0.003
		(0.009)
Oil		0.222
		(0.187)
Msciworld		-0.007
		(0.012)
VIX		-0.234
		(0.196)
USEPU		-0.002
		(0.003)
Twitter_senbtimenbt		-10.547
		(10.617)
SHIB_Trenbds		0.013
		(0.013)
Constant	0.187	63.648
	(0.112)	(64.095)
Panel B: Fall		
SHIB_Returns	2.012***	1.894**
	(0.771)	(0.772)
Gold		-0.002
		(0.003)
Oil		0.007
		(0.025)
Msciworld		0.001
		(0.004)
VIX		0.004
		(0.032)
USEPU		-0.000
		(0.000)
Twitter_senbtimenbt		1.521**
		(0.683)
SHIB_Trenbds		0.002
		(0.001)
Constant	-0.106	-9.295**
	(0.037)	(4.133)

Note: This table provides estimated coefficienbts for the model specified in Eq.(1). The depenbdenbt variable is the 4-hourly net total directional connectedness for Shibcoin (SHIB). The key explanatory variable is the 4-hourly return for SHIB (SHIB_Returns). Control variables include the 4-hourly index change in the spot gold (Gold), the WTI Spot Crude Oil (Oil), the MSCI World (Msciworld), the CBOE S&P500 implied volatility index (VIX), the US economic policy uncertainty (US EPU), the Twitter senbtimenbt (Twitter_senbtimenbt) and the Google Trenbds for Shibcoin (SHIB_Trenbds). Panel A provides estimates of the models for the rising period. Accordingly, Panel B provides estimates of the models for the falling period. Model 1 provides estimates for univariate models of returns of SHIB (SHIB_Returns) and Model 2 provides estimates for the multiple regression including all variables. Sample period for rising is September 25th, 2021-October 25th, 2021. And sample period for falling is May 11st, 2021-May 21st, 2021 and November 7th, 2021-December 31st, 2021, respectively. Standard errors are givenb in parenbtheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2022.103191.

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