Bubbles and Crashes in Cryptocurrencies: Interdependence, Contagion, or Asset Rotation?

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ABSTRACT

Using a quantile vector autoregressive model to capture return dynamics in extreme market conditions, we find that the cryptocurrency market exhibits a high level of market connectedness. Bitcoin is a net transmitter of return spillovers during busts and a net receiver during booms. Analysis of the timing of bubble and crash periods uncovers the presence of interdependence and contagion effects. Asset dynamics is driven to a great extent by the technology, in particular the consensus protocol of cryptocurrencies. There is only limited evidence for asset rotation, and it involves mostly Ripple.

JEL classification: C32; F3; G15

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1. Introduction

The notion that cryptocurrencies will become a widely accepted medium of exchange has been a major draw for both institutional and retail investors. Indeed, the boom in early 2021 pushed the market capitalization of the sector past the 1 trillion US Dollar benchmark. Along this expansionary path, the cryptocurrency market has witnessed periods of explosive growth followed by crashes and complex dynamic relationships among its main constituents. While the literature has primarily focused on the time series properties of Bitcoin (see, e.g. Conlon and McGee, 2020; Damianov and Elsayed, 2020; Kalyvas et al., 2020; Koutmos, 2018a) a new strand of academic studies has recently emerged aiming to quantify the dynamic spillover effects among the major cryptocurrencies (see, e.g. Antonakakis et al., 2019; Koutmos, 2018b; Katsiampa et al., 2019a and 2019b; Kumar and Ajaz, 2019; Yi et al., 2018; Zieba et al., 2019).

In this paper, we contribute to this rapidly growing literature by explicitly accounting for a salient feature of cryptocurrency dynamics: the occurrence of bubbles and crashes. Incorporating this aspect into the analysis is warranted on several grounds. First, it adds to the understanding of market risk as the largest gains and losses in investor portfolios are sustained during boom-and-bust cycles. Second, it affords a better insight into the risks of investing in the sector as it uncovers interdependence and contagion effects. Finally, it identifies potential hedging opportunities though the detection of cryptocurrency rotation within the sector.

We focus on the cryptocurrencies with the largest capitalization which include Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Dogecoin (DOGE), Stellar (XLM), and Ripple (XRP). Our aims are (1) to measure directional spillovers, and (2) make a distinction between interdependence (comovement), contagion and asset rotation effects.

We measure directional spillovers using the concept of population connectedness proposed by Diebold and Yilmaz (2014) and adapted to the study of tail quantiles by Ando et al. (2018). It uses a vector autoregressive framework to assess the shares of forecast error variation in one cryptocurrency due to shocks arising the other assets. The concept of connectedness aggregates both contemporaneous and dynamic aspects of spillovers (see Diebold and Yilmaz 2014, p. 120) which we visualize in a table and a graph. To disaggregate the contemporaneous from the dynamic (contagion) effects, we further apply the time series concept of a market bubble proposed by Phillips et al. (2015) and focus on timing effects. This approach allows us to gain insights into contagion (sequential market moves in the same direction) and rotation effects (opposite sequential moves in different markets).

The nascent theory of cryptocurrency price dynamics distinguishes between systemic risk factors, and asset-specific (idiosyncratic) drivers of returns and analyze how they shape the dynamics of different categories of digital assets. Corbet et al. (2020) consider three types of digital assets. These assets are currencies whose primary use is financial payments; protocols whose primary role is serving as a platform on which other applications can be based, and decentralized apps which are built on already existing blockchains. In addition, they differentiate between mineable and non-mineable assets and study how the constituents in each of these groups react to US Federal Open Market Committee announcements of changes in interest rates (or quantitative easing) as well as the stock market. They establish that digital currencies do not react in an identical manner and cannot be viewed as a single entity within the cryptocurrency market. Larger-cap currencies, however, as the ones we study here, are mostly driven by idiosyncratic factors while mineable assets are found to be more susceptible to monetary policy volatility than non-mineable.

Irresberger et al. (2020) on the other hand, focus on three economic determinants of fundamental value: adoption, scale, and security. While Bitcoin leads in adoption, it lags in scale as its primarily functionality is related to payments. It offers little value to users interested in DeFi transactions, smart contracts, gaming, gambling, or data storage. These applications are supported by the Ethereum blockchain yet both Ethereum and Bitcoin are inferior in terms of speed and security when compared to Stellar which is the most secure blockchain. The speed of transactions depends on the consensus protocol used by cryptocurrencies which also influences energy expenditure. Bitcoin uses proof of work while Ethereum transitioned to proof-of-stake protocol at the end of 2020 to improve energy efficiency. Litecoin and Dogecoin use proof of work while Ripple and Stellar use nonstandard protocols that verify transactions much faster and are more energy efficient.

With these technological differences in mind, we expect that our results will depend on the applications that cryptocurrencies support as well as on their protocols which determine both speed and energy consumption. In line with the extant literature, we would expect that Bitcoin is not a market leader anymore. It might be transmitting but also receiving spillovers from Ethereum which comes second in terms of market cap, but supports a wider range of applications. Furthermore, market booms would be led by innovations in the sector, and hence by the cryptocurrencies relying on the proof of stake protocol and the non-standard protocols. Market busts, on the other hand, could be led by global market risk factors and affect first the more established, large cap cryptocurrencies such as Bitcoin. In addition, Stellar and Ripple are expected to behave differently from the rest of the cryptocurrencies and from each other as they are based on nonstandard protocols. Spillover, interdependence and contagion effects are expected to be stronger across

Bitcoin, Ethereum, Litecoin and Dogecoin as all of them are based on the proof of work protocol, while asset rotation are expected to be observed between these assets and Stellar and Ripple.

As we are interested in examining the tails of return distributions, we use the quantile vector autoregressive model proposed by Ando et al. (2018) to estimate return spillovers. In accordance with the extant literature, we find that cryptocurrencies are highly connected with each other also when we look at the extreme (5 percent) lower and upper quantiles of return distributions. Bitcoin is a net transmitter of return spillovers during bear markets, and a net receiver during bull markets. Ethereum and Litecoin are net transmitters while Dogecoin and Ripple are net receivers both in bull and in bear markets. In a nutshell, empirical results from the spillover analysis show that cryptocurrencies are highly connected and interlinked under different market conditions. On average, more than three quarters of the total forecast error variance is attributed to spillovers and connectedness among cryptocurrencies. This motivates us to further investigate the nature of the connectedness and whether it’s interdependence, contagion, or asset rotation relationship among each pair of the cryptocurrencies. This information is of paramount importance to investors and portfolio managers searching for alternative assets to hedge against risk transmission during extreme periods (Bouri at al., 2020).

To further disaggregate the dynamics of the sector, we use the methodology by Phillips et al. (2015) to date-stamp the bubbles and crashes of individual cryptocurrencies. This allows us to distinguish between market interdependence (synchronized booms and busts), contagion (consecutive booms and busts) and asset rotation (boom in one currency followed by bust in another and vice versa) in the cryptocurrency market. We find evidence for interdependence and contagion particularly during booms and to a lesser extent during busts. There is only limited evidence for asset rotation which mostly concerns the Bitcoin-Ripple pair.

The remainder of the paper is structured as follows. Section 2 explains the econometric methods. Section 3 discusses data and empirical findings. Section 4 concludes and provides some policy implications.

2. Methodology

2.1 Modelling tail return spillovers

Spillover effects in cryptocurrencies are typically estimated with the approach of Diebold and Yilmaz (2012, 2014) which is based on forecast-error variance decompositions of a VAR model (see, e.g. Antonakakis et al., 2019; Elsayed et al., 2020; Fousekis and Tzaferi, 2021; Mensi et al., 2021; Yi et al., 2018). Despite the advantages and the popularity of this approach, it does not represent well the patterns of return spillovers under extreme market conditions. To study the return dynamics in the tails, we apply the *quantile connectedness* measure proposed by Ando et al. (2018) for the lower and upper quantiles (0.05 and 0.95) of returns. A quantile regression is used to estimate the dependence of a variable (y_t) on another variable (x_t) at each quantile (τ) of the conditional distribution of $y_t \mid x_t$ (Bassett and Koenker, 1978). A Quantile-VAR model of order p can be written as

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + e_t(\tau), \tag{1}$$

whereby y_t presents N-vector of endogenous variables. In our application $y_t = (\Delta P_{1t}, \Delta P_{2t}, \dots \Delta P_{6t})$ where $\Delta P_{jt} = P_{jt} - P_{j(t-1)}$ is the difference in the log prices of cryptocurrency $j = 1,2,3,\dots,6$. Further $B_i(\tau)$ is an N×N dimensional coefficient matrix while $c(\tau)$ and $e_t(\tau)$ are N×1 vectors of intercepts and residuals, respectively, at quantile τ where $\tau \in (0,1)$. Our estimation approach follows Ando et al. (2018) who assume that the cross-sectional correlation between the residuals is driven by common factors and adapt the spillover approach of Diebold and Yilmaz (2012, 2014) to the quantile forecast error variance decomposition of their model.

2.2 Date Stamping Bubbles and Crashes

To determine the beginning and the end of bubble and crash periods, we apply the methodology of Phillips et al. (2015) which is based on the following regression equation:

$$\Delta P_t = \alpha + \beta P_{t-1} + \sum_{i=1}^{k} \varphi^i \Delta P_{t-i} + \varepsilon_t \tag{2}$$

Hereby P_t is the log cryptocurrency price at time t and $\Delta P_t = P_t - P_{t-1}$. The coefficients α, β and φ^i are estimated with OLS, k is the number of lags,[2] and the error term ε_t is assumed to follow a normal distribution. We apply the backward sup augmented Dickey-Fuller statistics (BSADF) to date stamp possibly multiple periods of booms and busts for each cryptocurrency during the available period (Phillips et al. 2015; Shi, 2017). Roughly speaking, for each day in the sample t, the BSADF test considers backward expanding time windows ending on day t, repeatedly calculates the corresponding ADF statistic, and selects its supremum. The periods of explosive and implosive behavior are the periods in which the supremum ADF test statistics exceed their critical values which are calculated with a Monte Carlo simulation based on 2,000 replications. We require a minimum window of three days for the classification of bubbles and crashes. We classify a bubble period as a period in which the price at the end of the period exceeds the price at the beginning of the period. Conversely, a crash is a period in which the end price is lower than the initial price.

2.3 Interdependence, Contagion, or Asset Rotation Analysis

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[2] Following Shi (2017), we select the lag order k, which accounts for serial correlation, by BIC while allowing for a a maximum lag order of six.

We use dummy variables to denote the boom (B) and crash (C) periods for each cryptocurrency. Our tests for the presence of interdependence, contagion, or asset rotation in the market are based on the following logistic regressions:

$$\log\left(\frac{\mathrm{P}(Y_t^s = 1)}{1 - \mathrm{P}(Y_t^s = 1)}\right) = \beta_0 + \sum_{i=1}^{5} \beta_i X_{i,t-l}^{g} + \varepsilon_t \tag{3}$$

where $s \in \{B, C\}$ indicates either a boom or a crash period. The indicator variable g could be either s or the complement of s as explained below. The dummy variable Y_t^s represents one of the cryptocurrencies while the dummy variables $X_{i,t}^{g}$ for $i = 1,2,\dots,5$ represent the other cryptocurrencies. When interdependence and contagion effects are present, booms (busts) in one cryptocurrency occur simultaneously or with a lag with the booms (busts) in the other cryptocurrencies. We study these effects by estimating the regression specification for which $g = s$. The interdependence is a contemporaneous effect, and in these regressions $l = 0$, while the contagion is an effect occurring with a lag, which we assume to be one week, and therefore run the $l = 7$ specification. Rotation, on the other hand, is an effect in which a boom in one currency is associated with a simultaneous or lagged crash in another cryptocurrency and vice versa. Hence, in the contagion effects regressions g is the complement of s in the $\{B, C\}$ set. Similar analysis is performed in Bouri et al. (2019) yet limited to the detection of interdependence (termed "co-explosivity") in boom periods only.

3. Data and Empirical Results

We collected the daily closing prices for the aforementioned six cryptocurrencies from CoinMarketCap[3] for the period from June 1, 2016 to May 31, 2021. While we considered the top 20 cryptocurrencies by market capitalization, imposing the requirement that data should be

[3] https://coinmarketcap.com/

available during the entire period resulted in a sample of six currencies only. The descriptive statistics and correlation matrix of these cryptocurrencies is presented in Table 1.1. The return connectedness results for the extreme lower quantile are presented in Table 1.2 and for the extreme upper quantile in Table 1.3.

[Tables 1.1-1.3, about here]

The average return spillovers between cryptocurrencies under both bearish and bullish markets are quite high and account for 77.5% and 78.5% respectively. In other words, more than three quarters of the total forecast error variance is attributed to spillovers and connectedness among cryptocurrencies. These results are in line with previous literature that looks at the entire distribution of returns (see, e.g., Bouri et al., 2021; Elsayed et al., 2020; Fousekis and Tzaferi, 2021; Yi et al., 2018). A visual representation of these results is provided in Figure 1 in which we can identify the cryptocurrencies that are net transmitters as well as the ones that are net receivers of spillovers.

[Figure 1, about here]

As hypothesized, Bitcoin, which is the largest cap asset, is a net transmitter of return spillovers during busts and net receiver during boom periods. Stellar, on the other hand, which relies on a non-standard consensus protocol, is a net transmitter during booms and net receiver during busts. There is evidence that the price formation process, both in booms and busts is concentrated in specific currencies. Ethereum and Litecoin are net transmitters while Dogecoin and Ripple are net receivers of spillovers in both extreme market conditions.

We next turn to the analysis of bubbles and crashes. The results from the date-stamping procedure are presented in Figure 2. As can be observed, the methodology detects multiple periods of bubbles and crashes. The procedure detects the 2017 bubble that started in May that year for all cryptocurrencies, as well as the market crash which occurred in late 2018 and affected all cryptocurrencies except Ripple.

[Figure 2, about here]

[Tables 2.1-4.4, about here]

The analysis of interdependence, contagion and market rotation is presented in Tables 2.1.-4.4. Overall, there is strong evidence both for interdependence and for contagion during bubbles (Table 2.1. and 3.1). Bubbles in Bitcoin occur contemporaneously or are followed by bubbles in all other currencies except Ripple. There is less overall evidence for interdependence and contagion in market downturns (see Table 2.2 and 3.2) as these effects are constrained to the Ethereum-Bitcoin pair only which are the largest cap assets. Tables 4.1 to 4.4 present the analysis of asset rotation. The evidence for asset rotation mostly involves Ripple. Bubbles in Ripple coincide with crashes in Bitcoin (Tables 4.1 and 4.2). Indeed, Bitcoin, Ethereum and Litecoin all tend to crash after a bubble in Ripple (Table 4.4). Bubbles in the other currencies, however, do not cause Ripple to crash. Thus, Ripple plays a unique role as a diversifier in periods of severe downturns in the other cryptocurrencies. This result is in line with Mensi et al. (2020) who find that holding the Bitcoin-Ripple pair in a portfolio tend to reduce portfolio downside risk.

4. Conclusion

The cryptocurrency market has grown significantly in recent years. This growth was accompanied by bubbles and crashes along with complex dynamic relationships among the main constituents of the sector. In this paper, we disaggregate these dynamics and uncover interdependence and contagion effects in extreme market conditions. Our study highlights the critical role of the technology, in particular the consensus protocol, in the return relationships among the cryptocurrencies. There is less evidence for rotation effects, and they mostly involve the participation of Ripple. The use of a non-standard consensus protocol, the fast settlement and low fees makes this asset a good diversifier for the large cap cryptocurrencies (Bitcoin and Ethereum). Our analysis points to the limited opportunities for mitigation of the exposure to bubbles and crashes within the sector. We hope that this study will provide a foundation for further portfolio management applications that explore the extent to which tail risk can be managed by allocating funds to specific cryptocurrencies.

Table 1.1.
Descriptive Statistics and Correlation Matrix.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
Mean	0.232	0.398	0.290	0.202	0.306	0.285
Std. Dev.	4.129	8.076	5.745	5.961	7.8189	7.439
Max.	22.512	151.6210	29.013	51.035	72.315	102.746
Min.	-46.472	-51.49336	-55.071	-44.901	-41.004	-61.638
Skewness	-0.802	4.541	-0.532	0.367	1.876	2.080
Kurtosis	14.857	79.854	11.762	14.135	19.360	35.238
JB	10887***	455414***	5924.22***	9469.05***	21423.73***	80345.3***
ADF	-44.001***	-22.264***	-43.762***	-43.507***	-39.988***	-27.731***
PP	-44.000***	-41.445***	-43.887***	-43.548***	-40.075***	-44.605***
Q(10)	9.273*	23.673***	11.711**	15.492***	14.721***	24.794***
$Q^2(10)$	38.945***	40.193***	105.287***	67.129***	367.817***	202.813***
Correlation Matrix						
BTC	1					
DOGE	0.447	1				
ETH	0.645	0.403	1			
LTC	0.679	0.455	0.635	1		
XLM	0.456	0.416	0.477	0.484	1	
XRP	0.406	0.3569	0.439	0.471	0.614	1

Notes: This table reports descriptive statistics for the daily return series that are calculated as the first logarithmic difference between every two consecutive observations to ensure stationarity. J-B is the Jarque–Bera test for Normality. ADF and PP denote the empirical statistics of the Augmented Dickey-Fuller and Phillips-Perron unit root tests. Q(10) and $Q^2(10)$ are the Ljung–Box statistics for serial correlation in raw series and squared residuals. Finally, ***, **, * indicate significance at 1, 5, and 10% levels.

Table 1.2.
Return Connectedness in Quantiles (Extreme Lower Quantile $\tau = 0.05$).

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP	FROM others
BTC	21.68	14.70	16.95	17.10	15.17	14.40	78.32
DOGE	15.43	24.38	15.32	15.26	15.08	14.52	75.62
ETH	16.90	14.31	21.90	16.56	15.62	14.71	78.10
LTC	17.19	14.67	16.65	21.57	14.98	14.95	78.43
XLM	15.31	14.26	16.02	15.52	22.33	16.55	77.67
XRP	14.96	14.34	15.62	15.39	16.71	22.98	77.02
TO others	79.81	72.27	80.57	79.83	77.55	75.13	465.15
Inc. own	101.49	96.66	102.47	101.4	99.88	98.11	TCI = 77.53%
NET	1.49	-3.34	2.47	1.40	-0.12	-1.89	

Notes: This table presents empirical results of return spillovers between cryptocurrency markets. These results are based on the generalized forecast error variance decomposition (GFEVD) obtained from a Quantile-VAR model of order one with a 10-step ahead forecasts.

Table 1.3.
Return Connectedness in Quantiles (Extreme Upper Quantile τ = 0.95).

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP	FROM others
BTC	21.10	15.59	16.89	17.03	14.84	14.55	78.90
DOGE	15.09	22.26	15.56	15.65	16.10	15.33	77.74
ETH	16.34	14.98	20.79	16.67	15.62	15.60	79.21
LTC	16.67	15.00	16.69	21.48	15.25	14.90	78.52
XLM	14.65	14.98	15.8	15.68	21.78	17.11	78.22
XRP	14.48	14.87	16.10	15.69	17.10	21.76	78.24
TO others	77.23	75.43	81.04	80.73	78.91	77.49	470.82
Inc. own	98.33	97.69	101.83	102.21	100.69	99.25	TCI = 78.47
NET	-1.67	-2.31	1.83	2.21	0.69	-0.75	

Notes: This table presents empirical results of return spillovers between cryptocurrency markets. These results are based on the generalized forecast error variance decomposition (GFEVD) obtained from a Quantile-VAR model of order one with a 10-step ahead forecasts.

Table 2.1.
Logistic regression results: a cryptocurrency bubble dummy regressed on bubbles in the other cryptocurrencies.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
BTC		1.754***	1.155***	1.957***	2.834***	-1.187***
DOGE	1.697***		4.297***	-0.999***	0.084	2.372***
ETH	1.431***	4.094***		3.775***	1.236	1.636**
LTC	1.664***	-0.916***	3.966***		2.104***	2.200***
XLM	2.624***	0.004	2.257*	2.208***		1.424***
XRP	-1.727***	2.686***	3.122***	2.673***	1.501***	
Constant	-1.801***	-5.137***	-3.279***	-5.585***	-7.042***	-4.950***
McFadden's R-Squared	0.319	0.616	0.638	0.643	0.561	0.562
Observations	1,642	1,642	1,642	1,642	1,642	1,642

Notes: *** significance at the 1% level; ** significance at the 5% level; and * significance at the 10% level.

Table 2.2.
Logistic regression results: a cryptocurrency crash dummy regressed on crashes in the other cryptocurrencies.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
BTC			3.608***			
DOGE				2.036*	0.241	
ETH	3.608***					
LTC		2.036*			0.222	
XLM		0.241		0.222		
XRP						
Constant	-5.177***	-1.829	-3.791***	0.120	-1.829	
McFadden's R-Squared	0.181	0.123	0.083	0.136	0.005	
Observations	1,098	23	1,098	23	23	

Notes: *** significance at the 1% level; ** significance at the 5% level; and * significance at the 10% level.

Table 3.1.
Logistic regression results: a cryptocurrency bubble dummy regressed on lagged values of bubbles in the other cryptocurrencies.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
BTC$_{t-7}$		1.686***	1.407***	1.748***	1.794***	-1.042**
$DOGE_{t-7}$	2.068***		4.024***	-0.718**	0.847**	1.896***
ETH$_{t-7}$	0.517**	4.030***		2.907***	-0.244	0.593
LTC$_{t-7}$	2.355***	-1.691***	3.787***		2.772***	2.335***
XLM$_{t-7}$	1.212***	0.401	1.124	0.652*		1.314***
XRP$_{t-7}$	-1.241**	2.379***	1.802***	3.043***	1.042***	
Constant	-1.672***	-4.692***	-3.156***	-4.797***	-5.632***	-3.805***
McFadden's R-Squared	0.281	0.582	0.611	0.559	0.504	0.430
Observations	1,630	1,639	1,631	1,635	1,639	1,639

Notes: *** significance at the 1% level; ** significance at the 5% level; and * significance at the 10% level.

Table 3.2.
Logistic regression results: a cryptocurrency crash dummy regressed on lagged values of crashes in the other cryptocurrencies.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
BTC$_{t-7}$		1.335	3.553***			
$DOGE_{t-7}$	1.511					
ETH$_{t-7}$	3.430***			2.893**		
LTC$_{t-7}$		-1.705				
XLM$_{t-7}$						
XRP$_{t-7}$						
Constant	-4.457***	-1.335***	-3.736***	-5.201***		
McFadden's R-Squared	0.263	0.056	0.080	0.321	-0.223	
Observations	1,089	43	1,084	1,112	9	

Notes: *** significance at the 1% level; ** significance at the 5% level; and * significance at the 10% level.

Table 4.1.
Logistic regression results: a cryptocurrency bubble dummy regressed on crashes in the other cryptocurrencies.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
BTC						3.520***
DOGE						
ETH	0.306	4.014***				1.461
LTC						
XLM						
XRP						
Constant	-1.875***	-5.583***	-3.535***			-5.122***
McFadden's R-Squared	0.001	0.240	0.000			0.192
Observations	1,255	1,096	1,094			1,109

Notes: *** significance at the 1% level; ** significance at the 5% level; and * significance at the 10% level.

Table 4.2.
Logistic regression results: a cryptocurrency crash dummy regressed on bubbles in the other cryptocurrencies.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
BTC			-0.656			
DOGE			3.025***			
ETH	-17.420***					
LTC	22.010***					
XLM						
XRP	5.177***		2.825***			
Constant	-5.177***		-3.677***	0.154		-3.308***
McFadden's R-Squared	0.351		0.080	-0.000		-0.000
Observations	1,132		1,285	13		85

Notes: *** significance at the 1% level; ** significance at the 5% level; and * significance at the 10% level.

Table 4.3.
Logistic regression results: a cryptocurrency bubble dummy regressed on lagged values of crashes in the other cryptocurrencies.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
BTC$_{t-7}$						
$DOGE_{t-7}$						
ETH$_{t-7}$	0.469	4.024***				
LTC$_{t-7}$						
XLM$_{t-7}$						
XRP$_{t-7}$						
Constant	-1.722***	-6.969***	-3.266***			-4.564***
McFadden's R-Squared	0.001	0.182	0.000			0.000
Observations	1,247	1,084	1,088			1,067

Notes: *** significance at the 1% level; ** significance at the 5% level; and * significance at the 10% level.

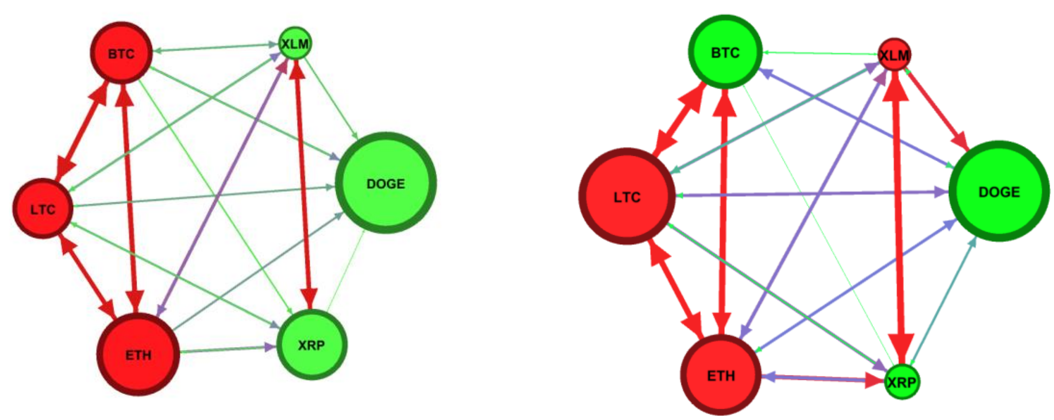
Table 4.4.
Logistic regression results: a cryptocurrency crash dummy regressed on lagged values of bubbles in the other cryptocurrencies.

Cryptocurrency	BTC	DOGE	ETH	LTC	XLM	XRP
BTC_{t-7}			-0.415			
$DOGE_{t-7}$			3.205***	4.115***		
ETH_{t-7}	-16.970***			-1.735***		
LTC_{t-7}	21.310***		3.219***			
XLM_{t-7}						
XRP_{t-7}	4.052***		2.221***	3.503***		
Constant	-4.457***		-3.651***	-5.729***		-3.308***
McFadden's R-Squared	0.276		0.010	0.423		0.000
Observations	1,122		1,282	1,128		85

Notes: *** significance at the 1% level; ** significance at the 5% level; and * significance at the 10% level.

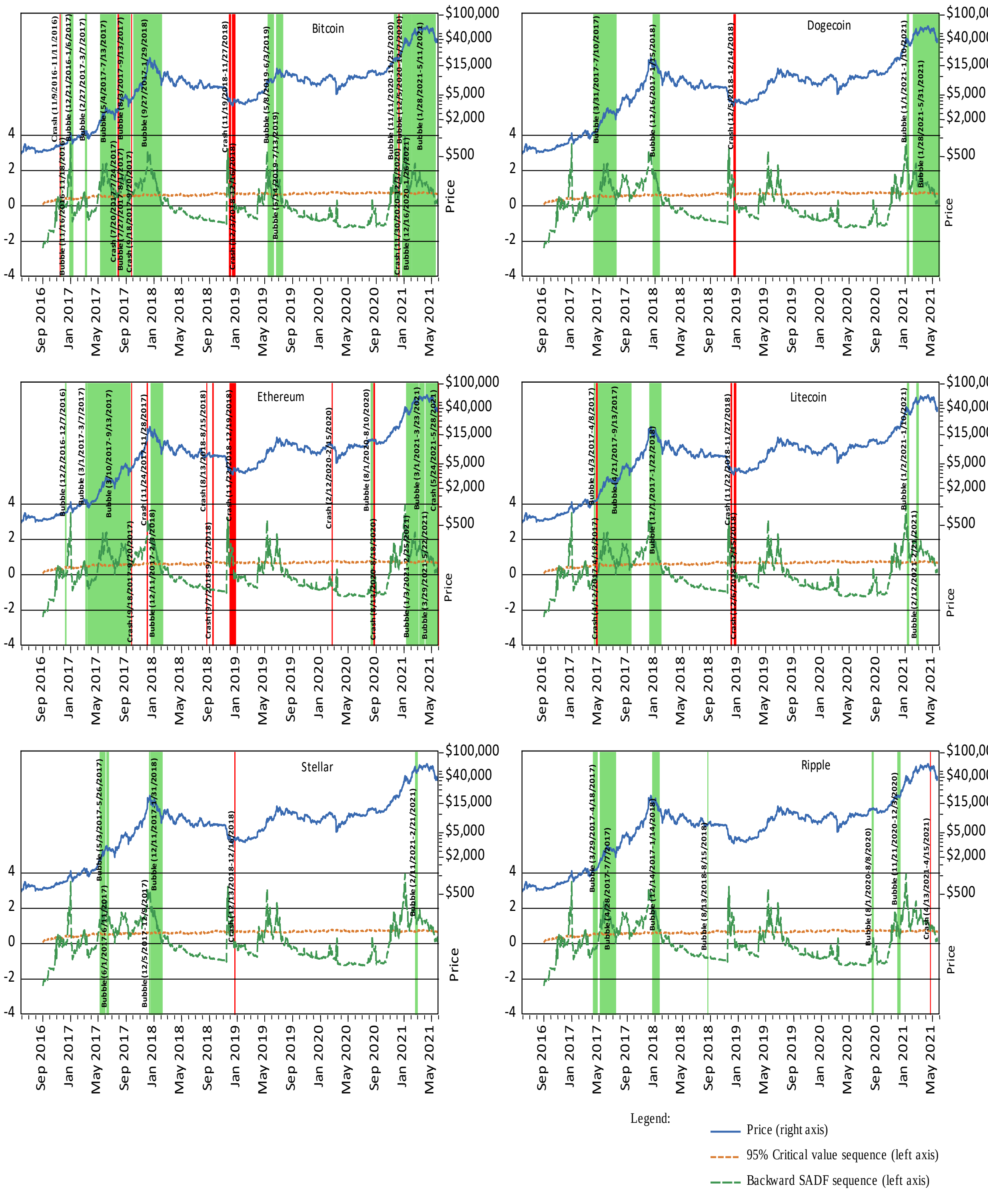
Fig.1. Directional pairwise spillovers network.

Panel A: Extreme Lower Quantile τ = 0.05	*Panel B:* Extreme Upper Quantile τ = 0.95



Notes: Panels A and B present the average pairwise directional spillovers among all possible pairs of the cryptocurrencies under bear and bull market conditions. A node's color identifies if a cryptocurrency is a net transmitter (red color) or receiver (blue color) of shocks to and from other cryptocurrencies. The size of the node shows the magnitude of net transmission/reception to/from other markets. Furthermore, the thickness and color of the arrows represent the magnitude and strength of the average spillover between each pair, respectively. In this case, the red color of the arrows indicates strong spillovers, the purple color shows moderate spillovers, and the green color refers to weak spillovers.

Fig. 2. Date Stamping of Bubble and Crash Periods for Cryptocurrencies, 2016m6-2021m5.



Note: When the BSADF test statics exceed the 95% critical value for at least 3 days, the corresponding periods have been shaded green (bubble periods) or red (crash periods).

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