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Crypto-environment network connectivity and Bitcoin returns distribution tail behaviour

Rocco Caferra [a,b], Andrea Morone [a], Valerio Potì [a,c,*]

[a] Department of Economics, Management and Business Law, University of Bari Aldo Moro, Bari, Italy
[b] Department of Economics, Universitat Jaume I, Castellón, Spain
[c] M. Smurfit School of Business, University College Dublin (UCD), Ireland

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ABSTRACT

This study explores whether and to what extent cryptocurrency ecosystem network connectivity predicts Bitcoin returns across quantiles of the return distribution. The facets of cryptocurrency ecosystem network connectivity we consider include connectivity between the on- and off-chain segments of the Bitcoin market, the intensity and synchronization of social and traditional crypto-focused media activity, the intensity of network correlations between cryptocurrencies. We identify tail behaviour predictors employing a quantile regression approach. The results demonstrate the effectiveness of several connectivity measures in predicting both price spikes and downfalls, but in a different way before and during the COVID-19 outbreak.

1. Introduction

Recent models of crypto-currency valuation[1] admit multiple equilibria in crypto-currency markets. In the model put forth by Cong et al. (2020), the source of equilibrium multiplicity is network externalities: transactional benefits[2] that accrue to holders of cryptocurrency increase with platform productivity, and this fact amplifies the impact of exogenous productivity shocks. This impact can be further amplified by the demand–supply spirals admitted by Pagnotta and Buraschi (2018). The model of Biais et al. (2019) emphasizes that transactional benefits (unlike, say, stock dividends) depend on the cryptocurrency purchasing power, and thus on its price. This generates the possibility of equilibria in which the price crashes to zero. Such equilibria occur if exogenous "sunspot" events trigger an extrinsic change in beliefs about both future prices and transactional benefits such that the current equilibrium price is zero. In the model of Biais et al. (2019), moreover, the time-varying probability of the sunspot can generate excess-volatility of the cryptocurrency price.

If these mechanisms are at play in crypto-markets, and if we view such markets and the broader ecosystem in which they operate as a network, then connectivity among the nodes of such network should influence tail returns. The relevant connectivity according to Cong et al. (2020) is between the on-chain and the off-chain segment of the cryptocurrency market. In the model of Biais et al. (2019)), this is complemented by connectivity between market participants provided by the media, through its role in the coordination of their expectations. To the extent that coordination of expectations occurs, at least to some extent, across the whole cryptocurrency market, measures of connectivity among the markets of different cryptocurrencies should also exhibit predictive ability for tail returns.

To test these predictions, we employ quantile autoregressions of Bitcoin returns augmented by measures of activity and connectivity of cryptocurrency markets and of the media that covers them. Our empirical results help identify the role of investors' connectivity and attention as drivers of market behaviour, highlighting however a change of dynamics between before and during the COVID pandemic.

2. Methodology

The quantile autoregressive model we employ is the following:

$$q_\tau\,(r_t \mid \Omega) = \alpha_\tau + \beta_\tau r_{t-1} + \delta_\tau Q_{t-1} + \lambda_\tau PCR_{t-1} + \eta_\tau MI_{t-1} + \theta_\tau MS_{t-1} + \zeta_\tau NT_{t-1} \tag{1}$$

* Corresponding author at: M. Smurfit School of Business, University College Dublin (UCD), Ireland.
E-mail addresses: rocco.caferra@uniba.it, al401530@uji.es (R. Caferra), andrea.morone@uniba.it (A. Morone), valerio.poti@ucd.ie (V. Potì).

1 See Liu et al. (2022) for a review.

2 These include censorship resistance and the ability afforded to the holder to engage in trustless exchange, as emphasized by Pagnotta and Buraschi (2018).

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In what follows, we first define the variables included in (1) and then explain the rationale for their inclusion. In (1), $q_\tau()$ is the quantile function conditioned to the $\tau \in (0,1)$ quantile, t is the time and Ω indicates the available information set. Returns (r_t) are calculated as the log differences of prices. We focus on Bitcoin as the representative cryptocurrency. Hence, the dependent variable is the Bitcoin log-return and the regression estimates are for the quantiles of the Bitcoin log-return distribution. Results with altcoin returns as dependent variables are available upon request. The parameters β_τ, δ_τ, λ_τ, η_τ, θ_τ, ζ_τ are the quantile coefficients associated to past returns (r_{t-1}), which we include to control for possible time-varying risk premia and/or slow processing of information, and the additional predictive variables. Q_t denotes the amount of Bitcoin on-chain transactions (Q_{t-1}). PCR_t is defined as $PCR_t \equiv \frac{Q_{e,t}}{Q_t - Q_{e,t}}$, where $Q_{e,t}$ is the amount of on-chain Bitcoin transactions involving exchanges (i.e., in which one of the addresses is the wallet of an exchange).[3] MI_t stands for *media incidence*, referring to incidence of crypto-related topics in the media. MS_t denotes synchronization of attention to cryptocurrency markets across the media. Regarding NT_t, it is defined as the probability that the nodes of the cryptocurrency network to which Bitcoin belongs are connected, akin to the transitivity (or clustering coefficient) in a graph (Csardi et al., 2006).[4] This probability is estimated using a DCC-GARCH network correlation model, as explained in Appendix A.

In the models of both Cong et al. (2020) and Biais et al. (2019), beliefs about transactional benefits play a key role, akin to the role of beliefs about fundamentals in the valuation of other assets classes (e.g., dividends in the case of stocks). The rationale for the inclusion among the regressor of Q_{t-1} is thus that it is a proxy for the amount of (expected) transactional benefits. That is, Q_{t-1} controls for the value of the Bitcoin as a medium of exchange.

If the switch between different possible equilibria[5] takes place on the on-chain segment of the cryptocurrency market rather than the off-chain one, as essentially implied by the model of Cong et al. (2020), we expect a measure of their connectivity, namely PRC_t, to predict returns in either tail. This corresponds to the anecdotal evidence that high flows between the on-chain and off-chain segments of the market predict extreme returns. This is the rationale for the inclusion of the lag of this variable in (1).

In the model of Cong et al. (2020), beliefs about transactional benefits are anchored by beliefs about platform productivity, whereas in the model of Biais et al. (2019) they depend on beliefs about future prices and, therefore, on how investors' expectations coordinate driven by (beliefs about) sunspots, as in the "temporary equilibria" emphasized by Brunnermeier et al. (2021). Thus, coordination of expectations plays essentially no role in the model of Cong et al. (2020), even in the event of interaction with the demand–supply spirals considered by Pagnotta and Buraschi (2018), whereas it plays a crucial role in the model of Biais et al. (2019). Therefore, the model of Biais et al. (2019) implies that tail thickness should depend also on media attention, as this is indicative of turning points in coordination of expectations. This is the rationale for the inclusion of MI_t, which measures *media attention towards cryptos*. For similar reasons, it may depend also on MS_t, which measures the extent to which media attention is synchronized across different media.

Beliefs about sunspots arguably change in similar ways across cryptocurrencies. For example, beliefs about changes to the regulatory stance are likely to affect beliefs about transactional benefits to holders of all cryptocurrencies. We thus expect measures of connectedness of cryptocurrency markets to correlate with equilibrium shifts, and thus to predict tail events, especially under the model of Biais et al. (2019).[6] In the quantile autoregression model, we thus include among the predictors NT_{t-1}, a measure of the extent to which the price changes of the cryptocurrencies are connected.

If the quantile coefficient of a given variable is positive for a certain range of quantiles, it means that the variable predicts higher values for those quantiles. Thus, a variable predicts fat tails in either direction if its quantile coefficients are negative on the downside (for low quantiles) and positive in the upside (for high quantiles). For example, under the model put forth by Biais et al. (2019), the coefficients of MI_{t-1} (η_τ) should be significantly positive (negative) for high (low) quantiles, implying that high (low) media intensity predicts returns in the positive (negative) tail. That is, the quantile coefficient should be increasing in the quantile. By the same logic, in the case of MS_{t-1}, the pattern we expect under the model of Biais et al. (2019) is different. We can expect attention to cryptocurrencies in the social and traditional media to converge on the upside and to diverge on the downside, in line with anecdotal accounts that Bitcoin raises enjoying the coordinated attention of all the media, but falls neglected by the traditional media. This is because market participants directly generate the content of social media like Twitter, hence their attention to crypto-related topics is likely not to fall (or even increase) when cryptocurrency markets fall, whereas the attention of traditional media likely fades in these circumstances. Coordination of expectation operated by the media can thus be expected to produce a U-shaped pattern in the quantile coefficients of MS_{t-1}, with positive and large coefficients especially for the lowest and highest quantiles.

3. Data

We obtain Bitcoin (BTC/USD) daily price index from www.coinmarketcap.com from the 02/02/2018 to the 17/04/2022. This gives a total amount of 1537 observations, though we treat the pre-COVID (02/02/2018 to 31/12/19) and the COVID (from 01/01/2020 onward) periods as distinct. We consider two distinct sample periods because of the evidence provided by earlier literature that the pandemic had a substantial effect on crytocurrency markets (e.g., Goodell and Goutte, 2021). To construct the network we then collect daily data on other 49 cryptocurrencies from the same website.[7] We also collect daily data on blockchain on-chain Bitcoin transactions from www.blockchain.com. We use this data to compute both Q_t, as the total volume of daily transactions in Bitcoin, and PCR_t, which is the fraction of these transactions that involve the 100 largest addresses. It is well known that these 100 largest addresses are mostly crypto-exchanges. Hence, PCR_t is an excellent proxy for the fraction of on-chain transactions in which one of the counterparties is

3 Exchanges are the interface between the on-chain and off-chain portion of the crypto-market. Thus, a large value of PCR_t means intense flow (hence, high connectivity) between the off-chain and on-chain segments of the Bitcoin market network. For example, if $PCR_t = 0$ ($PCR_t = 1$) it means that no (all) transactions on the cryptocurrency blockchain involve a crypto exchanges, implying no (full) connectivity between the blockchain and the off-chain market.

4 A value closer to 0 indicate a disconnected graph, while approaching to 1 it indicates the full graph connection.

5 Whether coordination of expectations play a role in addition to demand–supply spirals.

6 Borri (2019) found that crypto-currency returns are driven, in the tail of their joint distribution, by each other much more than by the returns on other asset classes.

7 These cryptocurrencies are: BitShares, BlackCoin, Dash, Diamond, DigiByte, DigixDAO, DNotes Dogecoin, DopeCoin, Emercoin, Ethereum, Expanse, Factom, Feathercoin, Goldcoin, Golem, Gulden, LBRY Credits, Lisk,Litecoin, Megacoin, MonaCoin,Navcoin, Neo, Nxt, Omni, Peercoin, Primecoin, Siacoin, Stealth, Steem, Stellar, Stratis, Syscoin, Terracoin, Vertcoin, Viacoin, Waves, WhiteCoin, Augur, Quark, XRP, Zcash, bitCNY, GameCredits, Gridcoin, NEM, NuBits, Verge.

Table 1
Descriptive statistics.

Variable	Mean	Standard Deviation	Minimum	Maximum	AC1
Returns (R_t)	0.00	0.04	−0.46	0.17	−0.059
On-chain Transactions (Q_t)	294519.70	46475.84	124640	452646	0.953
PCR_t	0.03	0.02	0.00	0.24	0.876
Tweets (TW_t)	61565.66	52698.04	13294	363566	0.916
Press incidence (PI_t)	0.10	0.04	0.03	0.40	0.751
Media synchronization (MS_t)	0.20	0.17	−0.25	0.58	0.932
Network transitivity (NT_t)	0.77	0.07	0.47	0.92	0.932
COVID-19 deaths	7537.14	3706.21	0	18144	0.90

the wallet of a crypto-exchange. Our proxy for MI_t is either the number of crypto-related Tweets, denoted by TW_t, or the incidence of crypto-related articles in the traditional (i.e., non social media) press, denoted by PI_t. Our proxy for MS_t is the DCC-GARCH correlation between the measure of *social* media attention towards cryptos, TW_t, and the measure of *traditional* media attention towards cryptos, PI_t, as better explained in Appendix A. We obtain the number of tweets from www.bitinfocharts.com,[8] while data on the international media incidence of the "cryptocurrency" theme have been sourced from the GDelt Project https://www.gdeltproject.org/.[9] Table 1 reports descriptive statistics.[10] We proxied for the COVID-19 severity considering the worldwide number of COVID-related deaths from https://ourworldindata.org/.

4. Results

We report here below estimates of (1) using daily data, for both the 2018–2019 and 2020–2022 sample periods. For the latter, we augment (1) with the COVID-19 deaths variable. Estimates with data at the weekly frequency are available as supplementary material.

4.1. Network effects across quantiles

We estimate the quantile regression in (1) with the quantile threshold ranging from $\tau = 0.05$ to $\tau = 0.95$. We report the estimates across quantiles of all the coefficients of the model where the proxy for media incidence is the number of relevant tweets, namely the case where $MI_{t-1} = TW_{t-1}$. For the case in which $MI_{t-1} = PI_{t-1}$, they are very similar and available upon request. Robust standard errors have been estimated using the bootstrap method.[11] In the estimated regression model, the variables Q_{t-1}, TW_{t-1} and the number of covid related deaths are normalized by dividing them by their respective maximum value over the sample period, in order to render the order of magnitude of their coefficients more easily comparable.

Fig. 1 reports results for both periods, before and after the outbreak of the COVID-19 pandemic. The reported results show that measures of connectivity predict Bitcoin returns in the tails of their distribution, but not always in a way consistent with the models of either (Cong et al., 2020) or (Biais et al., 2019).

In the pre-COVID period, the proxy for on-chain activity, Q_t does not predict tails returns to any appreciable extent. In the COVID period, it does but in an opposite way to the one compatible with the demand–supply spirals of Cong et al. (2020). In fact, the estimated quantile coefficients imply that higher on-chain activity shortens the tails, in either direction. Regarding PCR_t, the results are more supportive of the model of Cong et al. (2020): the estimates imply that it predicts longer tails both on the downside and the upside, though on the upside the effect is statistically significant only in the COVID period. Coming to MI_t, the results are supportive of the model of Biais et al. (2019): the estimates imply that media attention predicts returns in both the upper and lower tail, pointing to an important role of the media[12] in driving coordination of expectations. The U-pattern in the quantile coefficients of MS_{t-1} is also exactly what we would expect under the type of coordination of expectations operated by the media, under the assumed different role of the traditional and social media. The lack of a monotonically increasing pattern in the plot of the quantile coefficients of NT_{t-1}, however, is not what we would expect if coordination of expectations plays the key role in determining market switches across possible equilibria.

Our results for the COVID-period show that the pandemic affected both the upper and the lower tail. During this time, attention to pandemic-related developments might have replaced, at least to some extent, attention to crypto-market variables.

4.2. Coordination of expectations and price jumps

The lack of predictive ability of NT_{t-1} is, as noted in the previous sub-section, somewhat surprising. To investigate further, we propose a predictive quantile regression including as dependent variable the Bitcoin return at time $t + 1$ and, among the regressors, the interaction between the market regime at time t and the transitivity measure at time t. Specifically, we consider three different regimes: (i) a low regime, corresponding to returns falling in the first quartile of the distribution, (ii) an intermediate state, referring to the second and third quartile, and finally (iii) a higher state, considering the last quartile of the returns distribution. Results are reported in the heatmap in Fig. 2. The areas in blue denote large estimates for the interaction coefficient. Thus, the figure shows that the predictive ability of the transitivity measure, NT_t, is especially strong in low market states, and that high NT_t in low market states predicts a shift of the upper quantiles to the right, hence increasing skewness of the return distribution. Comparing the top and bottom panel, it can be observed that the effect is strong in low market states pre-COVID but largely vanishes during the pandemic. In a trading strategy this prediction could be exploited by purchasing at-the-money and out-of-the-money call options on Bitcoin when, in the low market return regime, NT_t increases, hence following low market returns and high values of NT_t.

8 We impute the previous observation in case of missing data.

9 See also Caferra (2020) who uses the same source. As explained in the website (https://www.gdeltproject.org/), this project is supported by Google and it monitors the world daily news. We selected the "Global Online News Coverage" database, and then queried the keyword "cryptocurrency". The output thus obtained is the number of daily news containing the topic identified by the keyword, normalized by the number of all the news monitored by the GDELT. The resulting value is then the share of the news items containing the cryptocurrency word over the total news scraped by the website.

10 For the sake of robustness, we control for the trend stationarity of the dependent variable, i.e. for Bitcoin returns.

11 We used the default method in the R function "boot.rq". This is the so called "xy-pair" method described by Kocherginsky et al. (2005)

12 Tweets, in this case, but also traditional media, as shown by the unreported results that are available upon request.

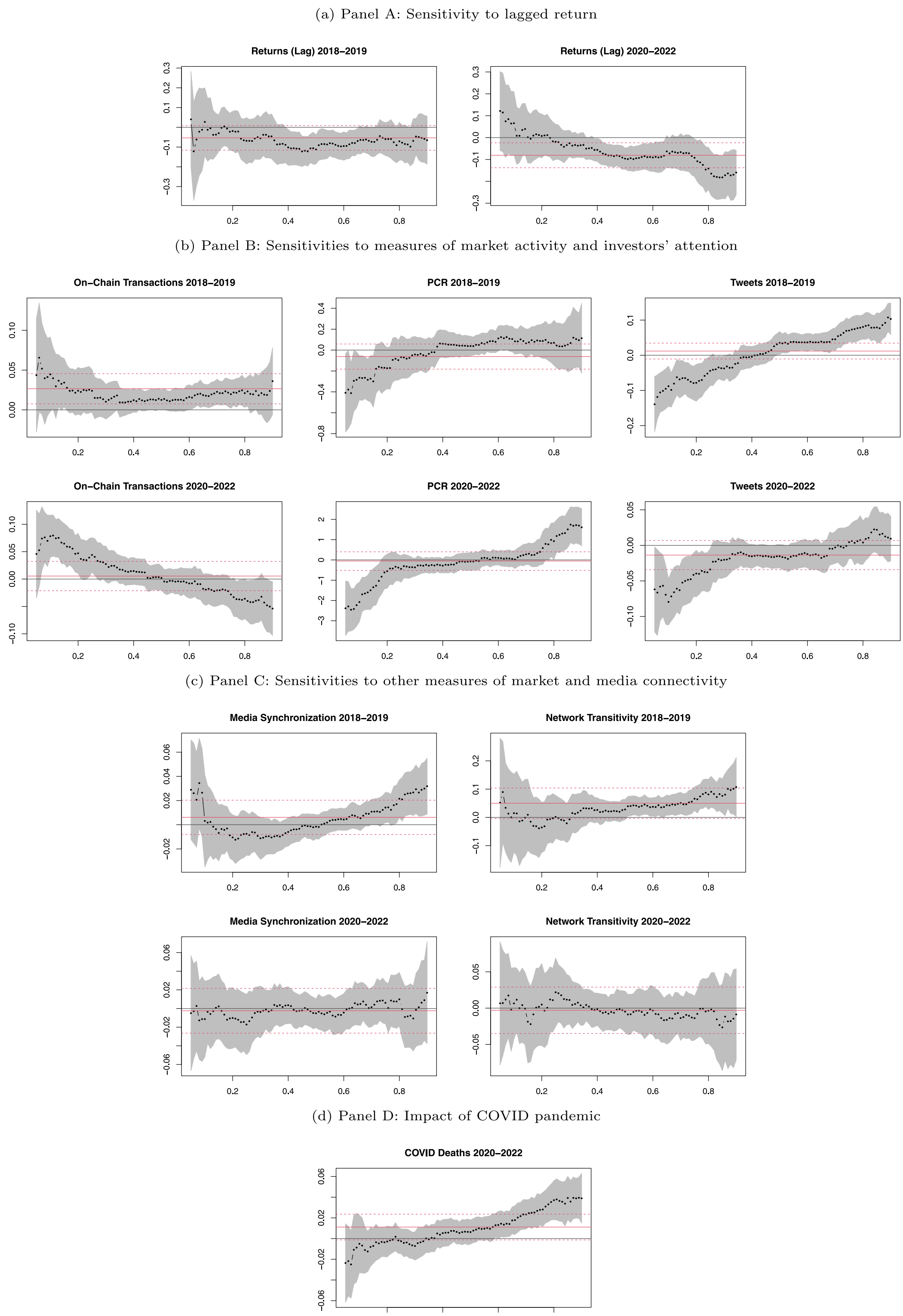

Fig. 1. Coefficients (y-axis) across quantiles (x-axis).

As it can be seen, while the effect of network transitivity is not statistically significant in the intermediate and high state, it turns statistically significant to explain price hikes following previous low market regimes. Hence, it is important to explain price jumps, consistent with the notion that increasing coordination of expectations leads to price jumps on the upside, a phenomenon sometimes associated with herding and bubbles.

5. Conclusions

By employing an approach based on quantile autoregressions, we have identified the role of network linkages in explaining Bitcoin tails behaviour. Our results are especially supportive of the possibility that coordination of expectations, as predicted by the model of Biais et al. (2019), plays an important role in

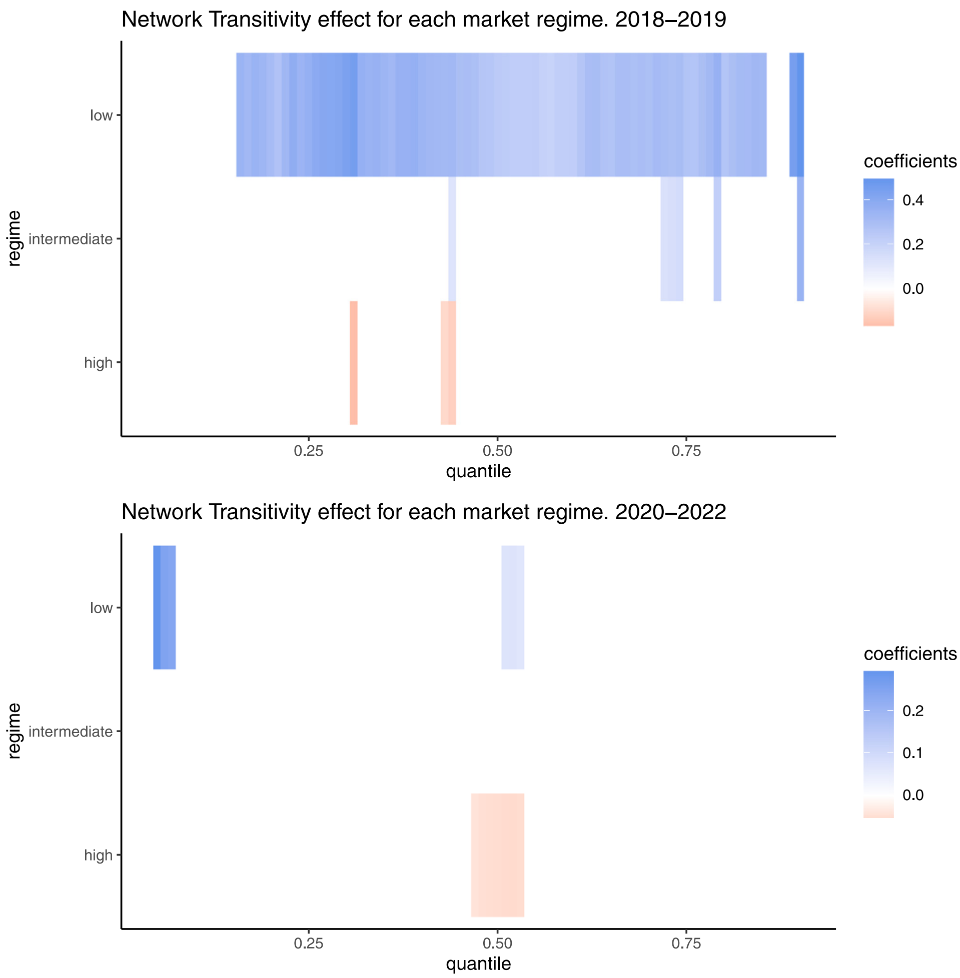

Fig. 2. Transitivity coefficients conditional on the three different market states at time t. "High" regime is the reference coefficient of the interaction. To help interpret the results, coefficients not statistically different from 0 (p-value > 0.10) have been reported as 0, hence showing non-zero estimates only for statistically significant coefficients.

explaining tail returns. We also show that Bitcoin returns on the upside are anticipated by increasing network connectivity, which we interpret as a proxy for convergence of expectations (the synchronization of the price dynamics) within the crypto ecosystem. We leave for future research to ascertain whether these empirical traits are unique to cryptocurrency markets, perhaps due to their relatively lower depth, lesser presence of professional investors, and/or absence of the stabilizing influence of a central bank, or are shared by financial markets more widely.

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Appendix A

A.1. Network connectivity

In asset correlation networks, the vertices are connected by weighted links, with weights given by the correlation coefficients between the returns of each pair of vertexes (i.e. assets), after defining a threshold above which ties (i.e., correlations) are deemed to be significant, indicating that a link exists. Following Lyócsa et al. (2012), we specify these correlation as conditionally time-varying, and estimate them using a dynamic conditional correlation (DCC) GARCH model of log-returns on the cryptocurrencies in our dataset. Our network is thus a Dynamic Correlation Network based on the daily log-returns of 50 cryptocurrencies (hence, with 50 vertexes) and weighted links based on the pairwise DCC, estimated using the full sample period. Among all the possible model specifications, after extensive specification tests (available upon request), we opt for a DCC-AR(1)-EGARCH(1,1) model. Following Vidal-Tomás (2021), we set a correlation threshold of 0.50[13] above (below) which a link is deemed to exists (does not exist). Our measure of global connectivity among cryptocurrencies is network transitivity (or the clustering

13 We consider also different higher thresholds. The results are similar and available upon request.

coefficient), NT_t, which is the probability that adjacent vertices of a network are connected (Csardi et al., 2006).[14] A value close to 0 indicates a disconnected graph while, if approaching 1, it indicates full graph connection.

A.2. Media synchronization

In a similar vein, we estimate the DCC over time of the two media attention measures we consider in our study, namely the number of Tweets (TW) and press incidence (PI). We estimate the DCC using a DCC-AR(1)-EGARCH(1,1) model based on the first differences of both variables (to ensure their stationarity). Increasing DCC indicates increasing synchronization between the two media types. This captures how social media (i.e., Tweets) and traditional media beliefs about bitcoin converge.

References

Biais, B., Menkveld, A., Casamatta, C., Bisiére, C., Bouvard, M., 2019. Equilibrium Bitcoin Pricing. Meeting Papers 360, Society for Economic Dynamics.

Borri, N., 2019. Conditional tail-risk in cryptocurrency markets. J. Empir. Financ. 50, 1–19.

Brunnermeier, M., Farhi, E., Koijen, R.S., Krishnamurthy, A., Ludvigson, S.C., Lustig, H., Nagel, S., Piazzesi, M., 2021. Perspectives on the future of asset pricing. Rev. Financ. Stud..

Caferra, R., 2020. Good vibes only: The crypto-optimistic behavior. J. Behav. Exper. Finance 28, 100407.

Cong, L.W., Li, Y., Wang, N., 2020. Tokenomics: Dynamic adoption and valuation. Rev. Financ. Stud. 34 (3), 1105–1155.

Csardi, G., Nepusz, T., et al., 2006. The igraph software package for complex network research. InterJ., Complex Syst. 1695 (5), 1–9.

Goodell, J.W., Goutte, S., 2021. Co-movement of COVID-19 and bitcoin: Evidence from wavelet coherence analysis. Finance Res. Lett. 38, 101625.

Kocherginsky, M., He, X., Mu, Y., 2005. Practical confidence intervals for regression quantiles. J. Comput. Graph. Statist. 14 (1), 41–55.

Liu, Y., Tsyvinski, A., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. J. Finance 77 (2), 1133–1177.

Lyócsa, Š., Vỳrost, T., Baumöhl, E., 2012. Stock market networks: The dynamic conditional correlation approach. Physica A 391 (16), 4147–4158.

Pagnotta, E.S., Buraschi, A., 2018. An Equilibrium Valuation of Bitcoin and Decentralized Network Assets. Technical Report.

Vidal-Tomás, D., 2021. Transitions in the cryptocurrency market during the COVID-19 pandemic: A network analysis. Finance Res. Lett. 101981.

[14] For robustness, we also consider the normalized network density obtaining similar results.