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Do investor sentiments drive cryptocurrency prices?

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Abstract

This paper studies the dynamic network connectedness between cryptocurrency returns and sentiments using the novel cryptocurrency-specific MarketPsych sentiment data for 13 cryptocurrencies with the highest market capitalization. The results indicate the dominance of cryptocurrencies with higher market capitalization and information transmission from cryptocurrency returns to sentiments. Our results also show that Bitcoin is losing its dominance to alt-coins in return spillovers while still dominant in sentiment spillovers.

Keywords: Cryptocurrency; Sentiment; Spillovers; TVP-VAR
JEL: C21, C22, G11, G14, G17

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1. Introduction

Network connectedness not only guides policymakers in designing their policies for financial stability but also helps investors and risk managers in making investment and hedging decisions [Ji et al., 2019, Corbet et al., 2020, Aslanidis et al., 2021]. Given its importance for investors and policymakers, there have been many studies on connectedness across various asset classes, but less so for cryptocurrencies. Moreover, unlike traditional assets, cryptocurrencies are not driven by economic fundamentals but move with investor sentiment [Burggraf et al., 2020, Bouri et al., 2021]. Yet, there are not many studies on the relationship between sentiment and cryptocurrency returns.

This paper contributes to the growing literature on cryptocurrencies by examining the connectedness among cryptocurrency returns and sentiments using the novel cryptocurrency-specific MarketPsych Indices as opposed to such studies as Corbet et al. [2020] and Lin [2020] utilizing Google Trend data. We suggest that cryptocurrencies with higher market capitalisation play a dominant role in total directional connectedness. Moreover, unlike such papers as Subramaniam and Chakraborty [2020], we find that the net overall information spillover effect transmits from cryptocurrency returns towards sentiments, i.e., cryptocurrencies are net transmitters. Furthermore, in terms of return connectedness, Bitcoin seems to be losing its dominance in the cryptocurrency universe, and the pendulum is swinging towards altcoins. Unlike the return connectedness, however, Bitcoin is the primary transmitter of sentiment shocks.

The paper is organized as follows: Section 2 presents the data. Section 3 introduces the methodology followed by the estimation results in Section 4. Section 5 concludes.

2. Data

Our data set consists of sentiment and (log) return series spanning the period January 1, 2018 - November 30, 2020 for the following cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), XRP (XRP), Litecoin (LTC), Stellar (XLM), Monero (XMR), Nem (XEM), Neo (NEO), Dash (DASH), Waves (WAVES), Zcash (ZEC), Ethereum Classic (ETC) and Dogecoin (DOGE). These are selected from the cryptocurrencies with the highest market capitalization for which data is available. This ensures that the sample covers a relatively long period and allows us to conduct our empirical analysis with more liquid cryptocurrencies. Daily return data is obtained from https://coinmarketcap.com, while daily sentiment data, which is created using mainstream news sources and social media in real-time, comes from MarketPsych Analytics. The sentiment score for each cryptocurrency ranges from -1 to 1.

3. Methodology

3.1. TVP-VAR-Based Dynamic Connectedness Approach

To construct dynamic connectedness measures, we follow the time-varying parameter vector autoregressions (TVP-VAR) approach of Antonakakis et al. [2020]. In particular, the TVP-VAR can be formulated as:

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

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

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

Furthermore, we compute the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) and transform the TVP-VAR to its vector moving average (VMA) representation based on the Wold theorem using the following equation: $z_t = \sum_{i=1}^{p} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j}$. The (scaled) GFEVD normalizes the (unscaled) GFEVD, $\phi^g_{ij,t}(H)$, in order that each row adds up to unity. Hence, $\tilde{\phi}^g_{ij,t}(H)$ represents the influence variable j has on variable i in terms of its forecast error variance share which can be defined as:

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\iota'_i A_t S_t \iota_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\iota_i A_t S_t A'_t \iota_i)} \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k} \phi^g_{ij,t}(H)}$$

where $\sum_{j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = k$, and ι_i corresponds to a selection vector with unity on the ith position and zero otherwise. Then, we compute the total connectedness index (TCI) through the use of the GFEVD as follows:

$$TO_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ij,t}(H) \tag{3}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ji,t}(H) \tag{4}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{5}$$

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt}. \tag{6}$$

where $\tilde{\phi}^g_{ij,t}(H)$ represents the impact a shock in variable j has on variable i. Eq.(3) illustrates the aggregated impact a shock in variable j has on all *other* variables which is defined as *total directional connectedness to others* whereas Eq.(4) indicates the aggregated influence all *other* variables have on variable j (*total directional connectedness from others*). Eq.(5) subtracts the influence *others* have on variable j from the impact variable j has on others and results in *net total directional connectedness*, providing information whether a variable is a net transmitter or a net receiver of

[1] The optimal 1-lag length is selected by the Bayesian information criterion (BIC).

shocks. Variable j is a net transmitter (receiver) of shocks and is therefore driving (being driven by) the network when its impact on others is larger (smaller) than the influence of all others on variable j, NETjt $>$ 0 (NETjt $<$ 0). Eq.(6) shows the TCI_t that is the average impact one variable has on all *others* or the average impact all others have on one variable. Higher values of this measure suggest higher inter-connectedness of the network, which means that a shock in one variable will influence others more.

4. Results

In this paper, we analyse three network structures inherent in Figures 1-3. In the first case, we examine the connectedness among cryptocurrency returns while we focus on the sentiments of these cryptocurrencies in the second case. In the third case, we evaluate the connectedness among cryptocurrency returns and sentiments combined. Fig. 1 shows that TCI attains its historical record of 88.15 at the beginning of the worldwide spread of Covid-19 around mid-March 2020. Remaining above 85 until mid-July, the values decrease with the relative easing of the pandemic conditions. Fig. 2-3 also show similar patterns for the second and third cases, respectively.

Tables 1-3 provide the time-averaged values of to, from, and net connectedness measures among cryptocurrency returns, sentiments, and cryptocurrency returns and sentiments combined, respectively. The numbers on the diagonal represent the impacts of shocks from one component of the network to itself, while the off-diagonal elements show spillovers among the network members. The numbers in column i display the impacts of a shock in the cryptocurrency return or sentiment i on the rest of the cryptocurrency returns or sentiments, described as the total directional connectedness *to others*, while those in row j show the impacts the rest of the cryptocurrency returns or sentiments have on the cryptocurrency return or sentiment j, described as the total directional connectedness *from others*. The numbers on the diagonal of Table 1 suggest that the own-variance shares of shocks for the cryptocurrency returns are in general higher (lower) for the less (more) liquid coins such as WAVES, DOGE, XEM (ETH, BTC, LTC). Moreover, concerning the spillovers among the network members, Table 1 suggests, for instance, that the highest spillovers to BTC are from ETH (9.52%) and LTC (8.96%). Similarly, the highest spillovers from BTC are to XMR (8.65%) and LTC (8.63%). Finally, we know that a net positive (negative) spillover value means that the network member is a net transmitter (receiver) of the shocks and hence leading (being led by) the network. The last row of Table 1 suggests that ETH, LTC, and XMR are the leading transmitters while WAVES, DOGE, and XEM are the largest shock receivers in the network. The numbers on the diagonal of Table 2 suggest that significantly large proportions of the spillovers result from cryptocurrency sentiments to themselves, and the remaining amount is mainly coming from the sentiments of the coins, which have relatively higher market capitalization. The net values of the sentiment indices, which are all very close to zero, support the above argument. Table 3 also shows similar conclusions for the combined network of cryptocurrency returns and sentiments.

Fig. 4 illustrates the network analysis of cryptocurrency returns. While each edge between two nodes demonstrates the net pairwise spillovers, the direction of arrows reflects which cryptocurrency receives shocks from which cryptocurrency on average. The edge thickness shows the strength of the connectedness between a pair of cryptocurrency returns so that thicker edges imply stronger net pairwise connectedness. Similarly, the size of each node illustrates the overall magnitude of net total directional connectedness for each cryptocurrency return, indicating that a cryptocurrency with a larger node size has a substantial role as the sender/receiver of shocks within the network. We highlight the nodes in red (green) if a cryptocurrency is a net transmitter (receiver) of the shocks within the system. The figure suggests that ETH, LTC, and XMR are the largest net transmitters of return spillovers, followed by BTC. This result implies that crypto-traders should focus on altcoins since their return movements influence the cryptocurrency market to a large extent. Our results also support the findings of Ji et al. [2019] which suggest that LTC has a dominant role in return connectedness despite its relatively smaller market size compared to BTC.

Fig. 5 shows the network analysis of cryptocurrency sentiments. Unlike in the case of return connectedness, BTC is the primary transmitter of sentiment shocks. This may result from the fact that cryptocurrency investors mostly follow the BTC news and social media tweets because of its popularity from being the first cryptocurrency. A more trivial explanation is that many investors could even be unaware of the presence of altcoins, which attract less attention due to their smaller trading volumes. Furthermore, altcoin prices tend to be highly volatile due to their smaller trading volumes, making them more vulnerable to "pump-and-dump" schemes. In such a scheme, these altcoins are heavily promoted by smaller groups via Reddit and Telegram, and hence their sentiments do not drive the overall cryptocurrency sentiments.

Fig. 6 presents the network analysis of cryptocurrency returns and sentiment indices together. The figure suggests that cryptocurrencies, except DOGE and WAVES, are the net transmitters of spillovers, whereas sentiments are the net receivers. One explanation could be that some delays in cryptocurrency transactions because of the required registration for public ledger absorb the effects of sentiments on cryptocurrency returns [Rognone et al., 2020]. [2] Fig. 6 also suggests that altcoin returns have a sizeable effect on the sentiment of BTC, implying that investor mood towards BTC is affected by the price movements of altcoins. Interestingly, ETH has a dominant role among cryptocurrencies, substantially influencing the sentiments of the leading cryptocurrencies such as BTC and LTC, indicating that BTC is losing its dominant position in the cryptocurrency universe and the price movements of Bitcoin do not drive the prices of altcoins. This result is also in line with the findings of Corbet et al. [2018] and Yi et al. [2018] showing that Bitcoin does not dominate the whole market in case of volatility spillovers.

[2]The average confirmation time for registration of buying and selling orders on the public ledger is 10 min.

5. Conclusion

This paper sheds light on the connectedness between cryptocurrency returns and sentiments and contributes to the cryptocurrency literature using the novel MarketPsych cryptocurrency-specific sentiment data. Our findings underline the dominance of cryptocurrencies with a higher market capitalization in total connectedness. As opposed to the widespread view in the literature, we show that information transmission is from cryptocurrency returns towards sentiments. A possible explanation is that delays in cryptocurrency transactions due to the required registration for public ledger absorb the effects of sentiments on cryptocurrency returns. Moreover, we find that while BTC is losing its dominance to altcoins in return connectedness, this is not the case for sentiment connectedness, possibly due to its popularity. COVID-19 pandemic has increased the connectedness of cryptocurrencies, especially during the early periods of the outbreak. Since September 2020, however, the cryptocurrency market has returned to pre-COVID connectedness levels. Besides, sentiment connectedness is more volatile than return connectedness implying the market is still nurturing with renewed interest in specific periods.

Our results have several implications. First, since the return movements of altcoins significantly impact the cryptocurrency market, crypto-traders should focus more on the performance of altcoins. Second, since ETH is the largest net transmitter of return spillovers, the price movements of ETH need to be followed explicitly by the investors. Despite its market cap dominance, BTC does not have a major role in transmitting shocks. Third, following the sentiments of just BTC suffices for investors. Sentiments formed in smaller communities in Reddit and Telegram are probably more informative for the investors of altcoins. Fourth, as the cryptocurrency market matures, BTC stands out more as a stable currency while providing less information on the market as opposed to leading altcoins like ETH, LTC, and XMR.

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Table 1: Average connectedness for the cryptocurrency returns.

	BTC	ETH	XRP	LTC	XLM	XMR	XEM	NEO	DASH	WAVES	ZEC	ETC	DOGE	from
BTC	15.63	9.52	6.19	8.96	6.06	8.84	5.22	7.28	7.26	5.58	7.08	6.88	5.47	6.49
ETH	8.49	13.68	7.46	9.07	6.58	8.07	6.06	7.92	7.52	5.01	7.70	7.84	4.62	6.64
XRP	6.65	8.99	17.21	7.89	8.93	7.28	6.49	7.11	6.26	4.14	7.13	6.83	5.08	6.37
LTC	8.63	9.80	7.04	14.86	6.40	7.85	5.81	7.42	7.22	5.01	7.36	7.48	5.12	6.55
XLM	6.67	8.02	9.09	7.27	17.14	7.83	6.51	7.29	6.10	5.04	6.99	6.68	5.36	6.37
XMR	8.65	8.82	6.69	7.96	6.96	15.02	5.36	7.22	8.34	5.22	8.16	6.91	4.68	6.54
XEM	6.38	8.38	7.29	7.41	7.27	6.69	19.68	7.51	6.30	4.31	7.00	6.90	4.90	6.18
NEO	7.55	9.27	6.89	7.97	6.93	7.68	6.25	16.53	7.20	4.74	7.31	7.00	4.68	6.42
DASH	7.56	8.78	6.19	7.89	5.86	9.00	5.35	7.20	16.30	4.46	9.77	6.98	4.66	6.44
WAVES	7.66	7.80	5.53	7.14	6.46	7.47	4.94	6.37	5.99	23.33	6.70	6.42	4.17	5.90
ZEC	7.28	8.82	6.69	7.84	6.51	8.50	5.80	7.14	9.34	4.74	15.57	7.43	4.34	6.49
ETC	7.38	9.38	6.81	8.29	6.53	7.54	5.94	7.13	7.08	4.83	7.77	16.40	4.91	6.43
DOGE	7.38	7.23	6.59	7.41	6.77	6.73	5.53	6.40	6.25	4.29	5.84	6.49	23.11	5.91
to	6.94	8.06	6.34	7.31	6.25	7.19	5.33	6.62	6.53	4.41	6.83	6.45	4.46	82.73
net	0.46	1.42	-0.03	0.76	-0.12	0.66	-0.85	0.19	0.09	-1.48	0.34	0.02	-1.45	

Table 2: Average connectedness for the sentiments of the cryptocurrencies.

	BTC-S	ETH-S	XRP-S	LTC-S	XLM-S	XMR-S	XEM-S	NEO-S	DASH-S	WAVES-S	ZEC-S	ETC-S	DOGE-S	from
BTC-S	70.39	8.37	1.89	9.05	1.86	1.47	0.84	1.75	0.60	0.73	0.34	1.90	0.82	2.28
ETH-S	8.06	73.63	1.99	5.11	2.22	2.12	1.02	1.06	0.60	1.07	0.66	1.50	0.96	2.03
XRP-S	2.84	2.66	80.16	3.02	2.56	1.29	1.74	1.25	0.83	1.19	1.35	0.42	0.68	1.53
LTC-S	8.04	6.29	2.10	72.89	1.70	1.28	0.63	1.62	1.01	0.98	1.21	0.89	1.36	2.09
XLM-S	1.03	2.01	2.80	1.79	85.44	0.97	0.92	0.72	0.40	0.72	0.95	0.82	1.42	1.12
XMR-S	1.65	2.12	1.18	1.05	0.96	84.46	0.68	0.76	0.69	1.46	2.42	1.00	1.58	1.20
XEM-S	1.15	0.99	1.75	0.80	0.58	0.75	87.83	1.42	1.63	1.01	1.10	0.35	0.65	0.94
NEO-S	2.22	1.89	1.24	1.30	0.60	1.18	2.06	85.82	0.60	0.49	0.78	0.91	0.92	1.09
DASH-S	1.59	0.87	0.95	1.22	0.57	0.87	1.20	0.94	88.22	0.93	0.93	0.81	0.89	0.91
WAVES-S	1.26	0.60	0.93	1.19	0.72	0.78	1.08	0.79	0.73	89.61	0.60	0.87	0.85	0.80
ZEC-S	1.41	1.39	1.20	1.37	0.74	3.16	1.43	0.93	1.32	0.75	82.98	1.83	1.48	1.31
ETC-S	2.28	1.49	0.91	1.07	1.04	1.09	0.33	1.05	0.73	0.78	1.62	85.53	2.09	1.11
DOGE-S	1.48	0.85	0.96	1.24	1.01	1.24	0.63	1.06	0.71	1.43	1.24	1.78	86.36	1.05
to	2.54	2.27	1.38	2.17	1.12	1.24	0.97	1.03	0.76	0.89	1.02	1.01	1.05	17.44
net	0.26	0.24	-0.15	0.08	0.00	0.05	0.03	-0.06	-0.15	0.09	-0.29	-0.11	0.01	

Table 3: Average connectedness for the cryptocurrency returns and their sentiments.

	BTC	ETH	XRP	LTC	XLM	XMR	XEM	NEO	DASH	WAVES	ZEC	ETC	DOGE	BTC-S	ETH-S	XRP-S	LTC-S	XLM-S	XMR-S	XEM-S	NEO-S	DASH-S	WAVES-S	ZEC-S	ETC-S	DOGE-S	from
BTC	15.06	9.16	5.93	8.60	5.75	8.44	5.01	7.05	6.99	5.31	6.85	6.61	5.24	1.81	0.54	0.25	0.51	0.13	0.08	0.12	0.12	0.08	0.11	0.07	0.14	0.05	3.27
ETH	8.19	13.22	7.15	8.68	6.29	7.72	5.77	7.66	7.25	4.87	7.46	7.54	4.46	1.33	0.62	0.26	0.60	0.13	0.11	0.12	0.15	0.09	0.07	0.10	0.13	0.06	3.34
XRP	6.38	8.63	16.68	7.55	8.55	7.00	6.23	6.86	5.99	3.98	6.93	6.59	4.92	1.14	0.48	0.45	0.46	0.15	0.16	0.14	0.15	0.12	0.11	0.14	0.12	0.10	3.20
LTC	8.30	9.41	6.72	14.39	6.09	7.53	5.58	7.14	6.91	4.80	7.09	7.19	4.95	1.37	0.60	0.30	0.73	0.11	0.10	0.10	0.12	0.12	0.08	0.08	0.15	0.05	3.29
XLM	6.33	7.68	8.67	6.91	16.55	7.50	6.24	6.99	5.83	4.84	6.77	6.40	5.12	1.22	0.61	0.36	0.57	0.28	0.17	0.21	0.12	0.13	0.09	0.15	0.17	0.08	3.21
XMR	8.31	8.47	6.46	7.65	6.69	14.57	5.12	6.95	8.01	5.07	7.83	6.67	4.47	1.46	0.46	0.30	0.47	0.12	0.11	0.12	0.14	0.09	0.07	0.09	0.14	0.12	3.29
XEM	6.13	7.97	6.95	7.08	6.97	6.35	19.05	7.14	6.00	4.19	6.73	6.56	4.66	1.30	0.39	0.36	0.60	0.15	0.10	0.28	0.22	0.19	0.15	0.11	0.20	0.15	3.11
NEO	7.35	9.00	6.65	7.68	6.67	7.39	5.97	16.03	6.95	4.58	7.07	6.78	4.49	1.32	0.43	0.22	0.50	0.15	0.08	0.16	0.11	0.06	0.07	0.09	0.13	0.08	3.23
DASH	7.34	8.52	5.98	7.58	5.64	8.64	5.10	6.97	15.79	4.28	9.41	6.68	4.45	1.26	0.50	0.36	0.49	0.10	0.12	0.11	0.16	0.13	0.09	0.07	0.15	0.07	3.24
WAVES	7.27	7.54	5.25	6.78	6.20	7.17	4.77	6.04	5.66	22.25	6.49	6.19	4.00	1.31	0.66	0.27	0.71	0.22	0.17	0.22	0.16	0.13	0.23	0.13	0.09	0.10	2.99
ZEC	7.05	8.55	6.52	7.54	6.30	8.13	5.58	6.90	8.97	4.62	15.05	7.09	4.22	1.22	0.45	0.31	0.43	0.13	0.17	0.11	0.10	0.10	0.06	0.15	0.17	0.09	3.27
ETC	7.11	9.02	6.54	7.95	6.25	7.24	5.62	6.88	6.74	4.69	7.40	15.82	4.75	1.59	0.56	0.22	0.66	0.19	0.13	0.12	0.08	0.09	0.06	0.08	0.14	0.08	3.24
DOGE	7.08	6.98	6.34	7.13	6.45	6.39	5.22	6.10	5.92	4.13	5.67	6.26	22.06	1.40	0.48	0.34	0.47	0.26	0.10	0.14	0.10	0.13	0.17	0.31	0.20	0.16	3.00
BTC-S	7.53	6.60	4.43	6.20	4.39	6.38	3.71	5.20	5.71	3.82	5.49	4.92	4.73	22.45	2.41	0.48	2.45	0.63	0.56	0.25	0.39	0.19	0.18	0.11	0.48	0.31	2.98
ETH-S	3.45	5.51	3.63	4.19	3.89	3.69	2.03	3.06	3.64	2.51	4.00	3.30	2.41	3.29	42.87	0.78	1.99	1.15	1.08	0.54	0.49	0.29	0.57	0.36	0.68	0.58	2.20
XRP-S	1.85	2.59	3.53	2.93	3.01	2.42	2.10	1.98	2.15	1.76	2.32	1.55	1.54	1.81	1.54	57.16	1.77	1.63	1.03	1.22	0.82	0.52	0.82	1.03	0.35	0.54	1.65
LTC-S	3.26	4.34	2.54	5.24	3.04	2.94	2.43	2.93	3.77	2.59	4.02	3.26	2.13	4.24	3.42	0.98	42.80	0.87	0.80	0.32	0.85	0.53	0.63	0.73	0.51	0.84	2.20
XLM-S	0.92	0.94	1.17	0.74	2.11	0.91	0.93	1.35	0.85	0.97	0.94	1.01	1.16	0.86	1.80	2.12	1.53	73.88	0.85	0.92	0.55	0.36	0.59	0.70	0.67	1.16	1.00
XMR-S	0.85	0.99	0.78	0.68	1.17	0.97	0.64	0.65	1.32	0.85	1.24	1.01	0.79	1.44	2.06	1.00	0.94	0.89	74.01	0.53	0.59	0.62	1.36	2.25	0.91	1.48	1.00
XEM-S	0.75	0.86	1.00	0.68	1.21	0.83	1.75	0.77	0.79	0.92	0.71	0.82	0.75	0.83	0.87	1.56	0.61	0.58	0.67	77.83	1.38	1.25	0.79	0.83	0.34	0.61	0.85
NEO-S	1.80	2.36	1.47	1.71	1.88	2.00	1.33	1.59	1.89	1.23	1.71	1.30	0.92	1.59	1.44	0.82	0.74	0.53	0.90	1.70	67.88	0.49	0.37	0.72	0.88	0.75	1.24
DASH-S	0.92	1.18	0.95	1.13	1.14	1.22	0.93	1.23	1.39	0.85	1.07	0.91	0.92	1.24	0.76	0.74	1.07	0.43	0.82	0.90	0.76	76.69	0.69	0.80	0.62	0.66	0.90
WAVES-S	1.13	0.79	0.81	0.96	0.77	1.07	0.91	0.69	0.69	1.41	0.68	0.55	0.90	0.88	0.66	0.80	1.01	0.61	0.75	0.96	0.69	0.63	79.65	0.51	0.77	0.70	0.78
ZEC-S	1.01	0.99	0.97	0.90	1.02	0.88	0.57	0.74	0.59	0.80	0.90	0.70	1.40	1.30	1.13	1.12	1.30	0.62	2.87	1.08	0.84	1.20	0.71	73.15	1.72	1.47	1.03
ETC-S	1.54	1.68	1.45	1.56	1.66	1.67	1.24	1.77	1.42	0.85	1.66	1.94	1.75	1.56	0.99	0.67	0.86	0.84	0.89	0.31	0.88	0.56	0.55	1.20	68.98	1.49	1.19
DOGE-S	0.52	0.61	0.75	0.58	0.67	0.73	0.62	0.61	0.71	0.46	0.64	0.62	1.01	1.36	0.72	0.84	1.10	0.83	1.12	0.58	0.95	0.63	1.16	1.12	1.70	79.36	0.79
to	4.32	5.01	3.95	4.56	3.99	4.43	3.28	4.05	4.08	2.86	4.27	3.94	2.93	1.47	0.95	0.61	0.87	0.45	0.54	0.43	0.42	0.34	0.38	0.46	0.44	0.45	59.49
net	1.06	1.68	0.74	1.27	0.78	1.15	0.17	0.82	0.84	-0.13	1.01	0.70	-0.07	-1.52	-1.25	-1.04	-1.33	-0.55	-0.46	-0.42	-0.82	-0.56	-0.41	-0.57	-0.75	-0.34	

Figure 1: Total connectedness of cryptocurrency returns

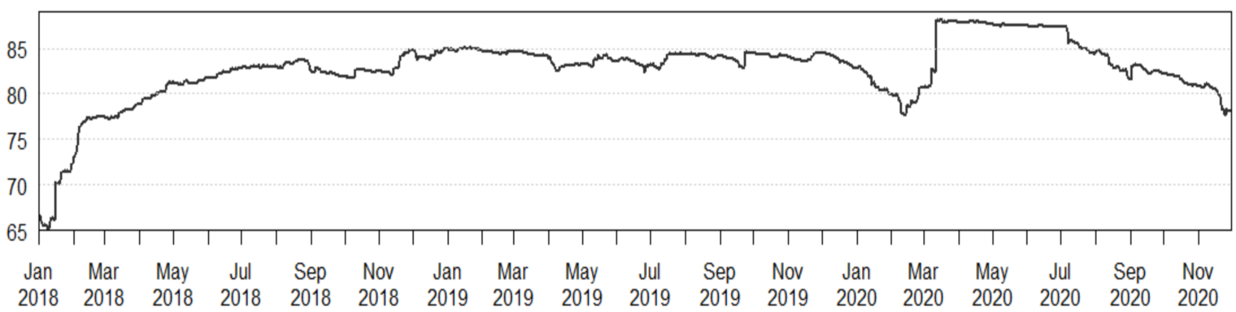


Figure 2: Total Connectedness of cryptocurrency sentiments

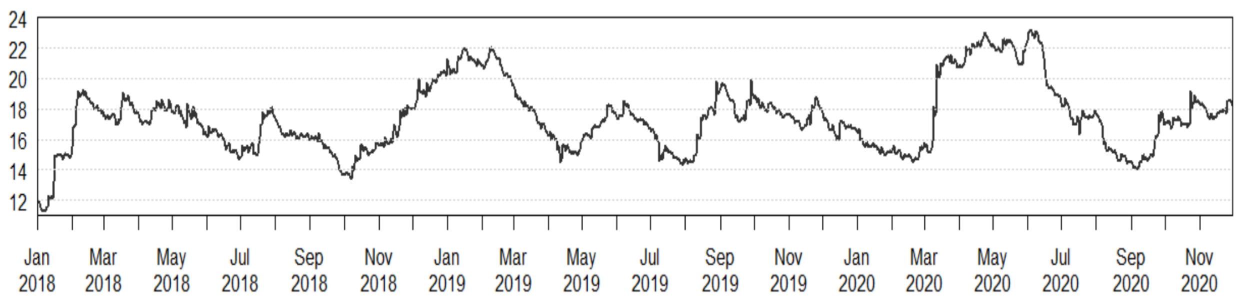


Figure 3: Total Connectedness of cryptocurrency returns and their sentiments

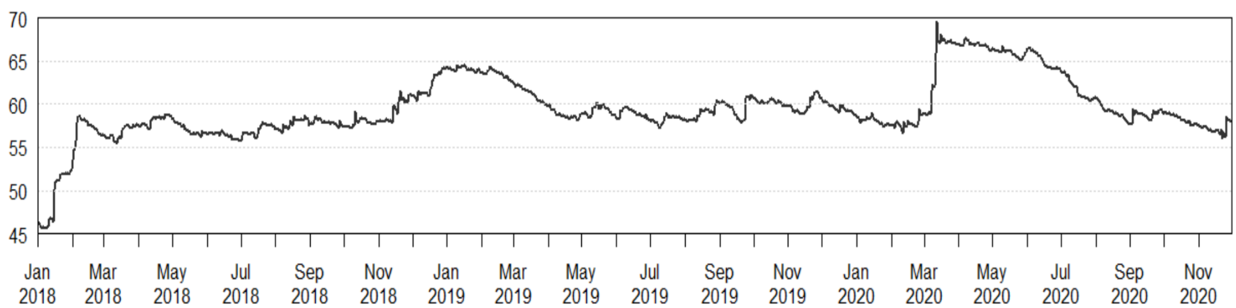
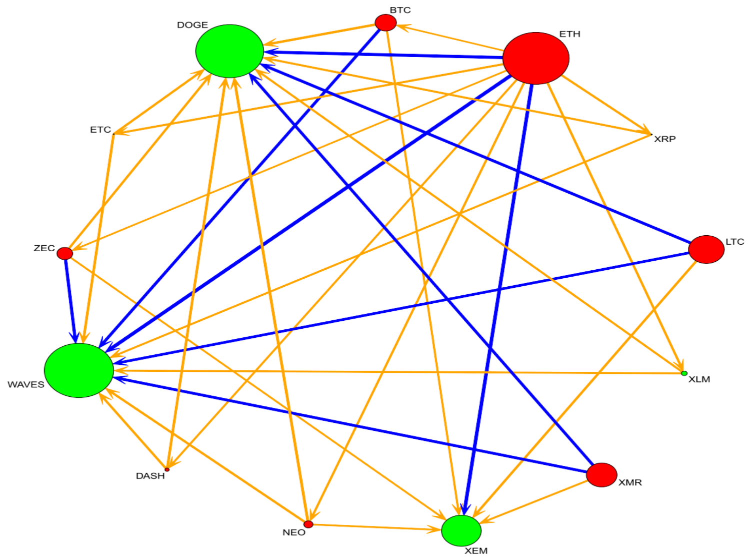
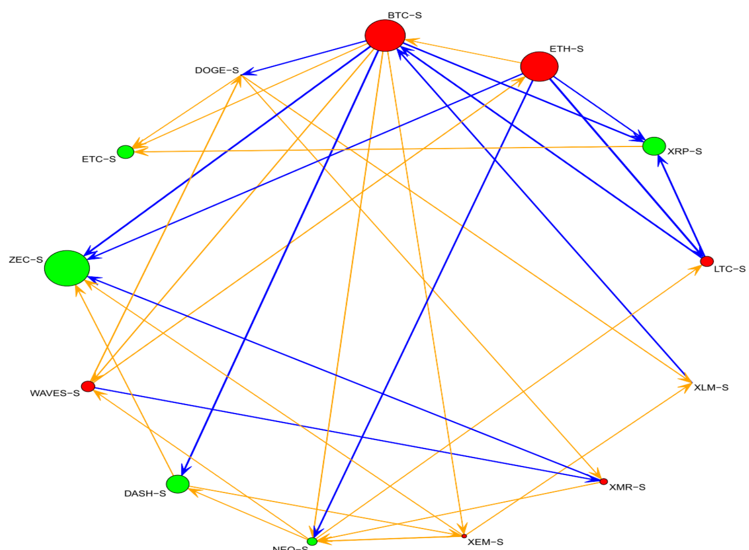


Figure 4: Network analysis of cryptocurrency returns



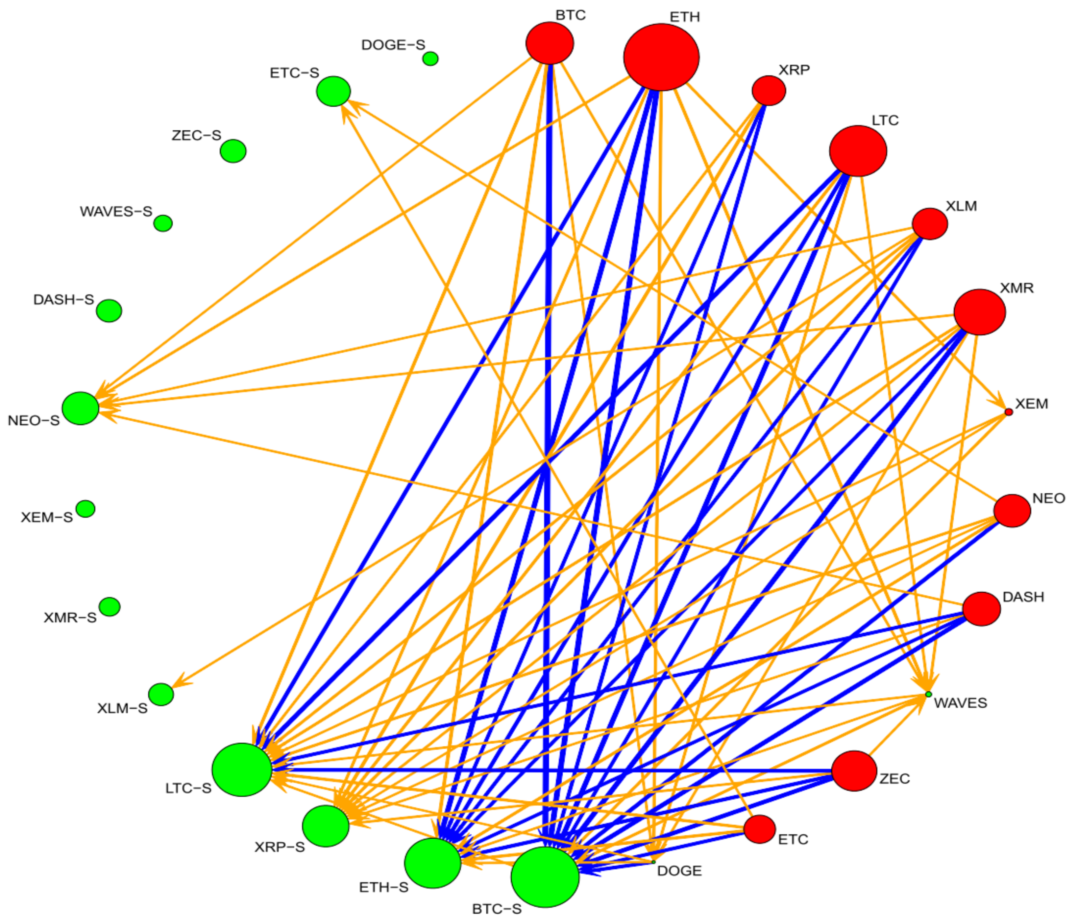
Notes: See notes to Fig. 6. In this case, the cut-off point is found to be 0.07. Therefore, we only plot the edges with values greater than 0.07 on this figure. Blue edges have a value greater than 0.15.

Figure 5: Network analysis of cryptocurrency sentiments



Notes: See notes to Fig. 6. In this case, the threshold point is found to be 0.04. Therefore, we only plot the edges with values greater than 0.04 on this figure. Blue edges have a value greater than 0.05.

Figure 6: Network analysis of cryptocurrency returns and their sentiments



Notes: For better visualization, we impose a 80% bound on the edge values after sorting the net directional spillover values from smallest to largest i.e. we only visualizes the top 20 % of the values. In our case, the cut-off point is found to be 0.06. Therefore, we only plot the edges with values greater than 0.06 on this figure. We further differentiate between these edges by coloring the ones of strength greater than 0.12 as blue and others as yellow.