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Nonlinear nexus between cryptocurrency returns and COVID-19 news sentiment

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ABSTRACT

The paper examines how various COVID-19 news sentiments differentially impact the behaviour of cryptocurrency returns. We used a nonlinear technique of transfer entropy to investigate the relationship between the top 30 cryptocurrencies by market capitalisation and COVID-19 news sentiment. Results show that COVID-19 news sentiment influences cryptocurrency returns. The nexus is unidirectional from news sentiment to cryptocurrency returns, in contrast to past findings. These results have practical implications for policymakers and market participants in understanding cryptocurrency market dynamics under extremely stressful market conditions.

1. Introduction

Signalling theory documents the importance of news as signals to perceive future market behaviour (Connelly et al., 2011). The framework asserts the role of the signaller and the signal, and whenever the signal contains new or vital information, the markets tend to react accordingly to new signals (Fu et al., 2021; Romer, 1993; Wei and Zhou, 2016). Numerous news signals are available in the public domain and are used to understand asset pricing behaviour (Gan et al., 2020; Sanford, 2020). Extant literature has supported that whenever news is unavailable in the public domain and it is released with a degree of surprise, the vibrancy in the markets is equally visible in prices and trading volume (García et al., 2014; Banerjee et al., 2020; Banerjee and Pradhan, 2020a, 2021a). The most prominent news market participants regularly follow in anticipation that news may have novelty are the economic and financial news (Banerjee and Pradhan, 2020a; Banerjee et al., 2021; Büttner and Hayo, 2010). The impact of such news on various asset classes such as bonds, currencies, stocks and futures markets is well-documented (Banerjee and Padhan, 2017; Banerjee and Pradhan, 2021a; Brenner et al., 2009; Luss and d'Aspremont, 2015).

Signalling theory remains a robust foundation for explaining investment decisions and strategic asset allocation (Alsos and Ljunggren, 2017; Frijns and Huynh, 2018; Griffith et al., 2020; Heston and Sinha, 2017), investor's underreaction or overreaction to news (see Barberis et al., 1998; De Bondt and Thaler, 1985; DeFond and Zhang, 2014; Miwa, 2019; Banerjee and Pradhan, 2020b). Recently studying the credit default markets (CDS), Marsh and Wagner (2016) have asserted that swap dealers exploit the informational advantages against investors. Wei and Zhou (2016) documented the surge in bond trading activity before the release of earning announcements in the expectation of information asymmetry in news signals. Bailey et al. (2014) reported a significant association between changes in the volatility index (VIX) and macroeconomic announcements by studying the high-frequency changes in VIX. Past literature has found a causal impact on financial journalism, media news and aggregate market prices (Banerjee et al., 2021; Dougal et al., 2012) and how management

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disclosures work as a signal that drives investors (Koonce et al., 2016). Some varied examples of signalling theory are initial public offering (IPO) pricing, news sentiments influencing stock returns at the aggregate market level (Cutler et al., 1989; Garcia, 2013; Tetlock, 2007) and the individual stock level (Boudoukh et al., 2013; Chen et al., 2014). Information uncertainty originating from news sentiment increases expected stock return, thus affecting stock returns negatively (Zhang, 2006). Thus, the above reinstates that information asymmetry remains the mainstay of signalling theory, with the information intent and quality the critical factors (Stiglitz, 2002).

Currently, the literature has begun exploring the impact of news on newer asset classes such as cryptocurrencies, which are drawing much attention for their diversification properties and hedging role. Moreover, the assumption that analysing the impact of news on cryptocurrency returns may reveal newer perspectives is gaining ground in the literature (Bouri and Gupta, 2019; Bouri et al., 2020; Naeem et al., 2021; Rognone et al., 2020; Salisu and Ogbonna, 2021). Over the past decade, cryptocurrencies have seen remarkable growth and received extensive attention from market players interested in determining the driving factors behind price formation (Aharon, 2020; Ciaian et al., 2016; Kristoufek, 2013; Raimundo Júnior et al., 2020; Subramaniam and Chakraborty, 2020; Youssef, 2020). However, cryptocurrencies have a unique price, volume, and risk features (Sifat, 2021). Due to this uniqueness, cryptocurrency valuation is challenging (Ciaian et al., 2016). In addition, the literature on the mechanism of how news and sentiment influence cryptocurrency return is evolving (Corbet et al., 2019; Naeem et al., 2020; Poyser, 2019). The present paper contributes to the debate on how news and sentiment affect cryptocurrency prices, especially during the COVID-19 pandemic.

Apart from examining the effect of news sentiment on cryptocurrency return, we attempt to determine whether the nexus is linear or nonlinear. Most studies examine the linear relationship (Corbet et al., 2020a). We anticipate a nonlinear relationship, and we use the Brock, Dechert and Scheinkman (BDS) test of Broock et al. (1996) to examine the nonlinear structure in the return series. The results of the BDS test reveal a nonlinear structure in the cryptocurrency return series. Hence, a nonlinear technique is better adapted to capture cryptocurrencies' return and volatility dynamics. We employ transfer entropy (TE), which measures asymmetric information flow and causality in complex systems (Kwon and Oh, 2012; Marschinski and Kantz, 2002). Though literature explored the information flow in financial markets, TE widens the possibility of detecting nonlinear relationships. Marschinski and Kantz (2002) use TE to measure the relationship between the U.S. Dow Jones Industrial Average and the German DAX Xetra Stock Index. In contrast, Kwon and Yang (2008) substantiated that the US stock market impacts major stock market indexes globally by applying TE. Sensoy et al. (2014) found a robust nonlinear relationship between exchange rates and stock prices.

The literature relating the COVID-19 pandemic to financial markets, including cryptocurrencies, has been evolving since the onset of the pandemic. For example, Corbet et al. (2020b) show that the COVID crisis has negatively impacted firms. Akhtaruzzaman et al. (2021a) report that firms across G7 countries and China significantly rose in conditional correlation. The study results support the findings of Banerjee (2021), who report that cross-market linkages cause contagion in futures markets in both developed and emerging countries. Apart from financial contagion during the pandemic, the literature shows the changing dynamics of gold as a safe-haven property (Akhtaruzzaman et al., 2021b). The pandemic moderates the oil price exposure of industries (Akhtaruzzaman et al., 2020a; Banerjee and Pradhan, 2021b).

Moreover, Goodell and Goutte (2021) emphasise that cryptocurrencies have failed to act as safe-haven assets during the COVID-19 period. Recent studies examine the interaction between cryptocurrency and other asset classes like foreign exchange, commodities, and stocks (Akhtaruzzaman et al., 2020b; Pho et al., 2021). Gajardo et al. (2018) propose a non-symmetrical association between Bitcoin and equity markets. Aste (2019) and Gkillas et al. (2018) report that intra-market correlation among cryptocurrencies exhibits non-normal statistical properties in price fluctuation. Some of the recent literature discusses the effects of COVID-19 on cryptocurrency markets (e.g., see Conlon et al., 2020; Lahmiri and Bekiros, 2020; Wang et al., 2019). Several authors analysed if the COVID-19 pandemic affected the relationship between cryptocurrencies. For example, Bouri et al. (2021b) applied quantile-based connectedness measures. They revealed that the connectedness measures in the left and right tails are much higher than those in the mean and median of the conditional distribution, indicating that return shocks propagate more intensely during extreme events relative to calm periods. Aslanidis et al. (2021) aimed to answer whether cryptocurrencies are becoming more integrated between August 2015 and July 2020. They find a substantial increase in market linkages for both returns and volatilities, indicating a tighter relationship among cryptocurrencies in the COVID-19 period. Demiralay and Golitsis (2021) investigated the time-varying comovements employing a dynamic equicorrelation GARCH (DECO-GARCH) model in crypto markets. The study results show that the comovements across cryptos increased substantially in the wake of the COVID-19 pandemic. However, most studies ignore the possibility of the relationship's nonlinear or asymmetric nature (Baur and Dimpfl, 2018). Changes in news content related to the COVID-19 crisis may have a differential impact on the prices of cryptocurrencies.

Akyildirim et al. (2021) studied the dynamic network connectedness between 13 leading cryptos by market capitalisation and MarketPsych indices. The results supported the dominance of cryptocurrencies with higher market capitalisation. However, Bitcoin was losing its dominance to altcoins in return spillovers while still dominating in sentiment spillovers. Moreover, past studies emphasised that Bitcoin is against other major cryptocurrencies that tend to have a significant presence in the market (Corbet et al., 2020a; Oad Rajput et al., 2020). However, there is a void in the literature studying the impact of different COVID-19 news sentiments on major cryptos. We address this void in this study by examining the nexus between the top 30 cryptocurrencies (constituting approximately 79% of total market capitalisation) and COVID-19 news sentiment obtained from the Ravenpack database. In contrast, some studies have found an association between other sources of news sentiment like Google Trend or MarketPsych indices and volatility (Akhtaruzzaman et al., 2021c; Akyildirim et al., 2021; Blitz et al., 2020; Philippas et al., 2019; Shi and Ho, 2021; Smales, 2014; Lin, 2021).[3]

The study is the first to analyse the differential impact of different categories of COVID–19 news sentiment on the behaviour of cryptocurrency returns. We investigate the reaction of the top 30 cryptocurrencies to COVID-19 news over the sample period from January 1, 2020 to April 15, 2021. The results indicate a significant positive nonlinear relationship between cryptocurrencies' return and news sentiment related to COVID-19. The results reflect that cryptocurrencies witnessed a bullish run during the study period, and some of these reacted more to COVID–19 developments. In particular, the media portrayal of COVID–19 conditions influences most cryptocurrency returns, which is more pronounced with Bitcoin Cash, DASH, Tether, and DAI.

Cryptocurrencies react vigorously to media exaggeration, where the recent Dogecoin fiasco represents a glaring example of market overreaction and herd behaviour (Hobbs, 2021). In

[3] Source: https://coinmarketcap.com/.

Table 1
Top 30 cryptocurrencies by market capitalisation.

Cryptocurrency name	Short name	Symbol	Market capitalisation (USD in Billion)
Bitcoin	BTC		$1,079.670
Etherum	ETH		$320.823
Binance Coin	BNB		$95.754
XRP	XRP		$72.268
Tether	USDT		$50.995
Dogecoin	DOGE		$43.682
Cardano	ADA		$43.208
Bitcoin Cash	BCH		$18.600
Litecoin	LTC		$18.101
Chainlink	LINK		$15.976
VeChain	VET		$12.932
Stellar	XLM		$12.166
THETA	THETA		$11.189
TRON	TRX		$9.475
Monero	XMR		$7.551
Terra	LUNA		$6.527
EOS	EOS		$6.140
IOTA	MIOTA		$5.973
Crypto.com	CRO		$5.009
BitTorrent	BTT		$4.779
Houbi Token	HT.		$4.359
Tezos	XTZ		$4.312
Etherum Classic	ETC		$4.230
Algorand	ALGO		$4.147
Dai	DAI		$3.834
THORChain	RUNE		$3.622
Dash	DASH		$3.226
Chilitz	CHZ		$3.183
NEM	XEM		$3.173
Stacks	STX		$2.440

Note: The market capitalisation of cryptocurrencies is based on April 15, 2021.

comparison, fake and sentiment news have the most negligible impact on cryptocurrencies compared to other news sentiment indices. Globally, the news sentiment related to the COVID-19 influence almost all the cryptocurrency returns, contradicting the finding of Akyildirim et al. (2021). Thus, these results hold valuable insights for market participants. Moreover, uncertainty became relatively high in Ripple and saw a sudden price spurt during the pandemic (Bouri et al., 2021a). The recent bullish run seen in cryptocurrency prices does not reflect fundamental value. These episodes suggest the presence of considerable speculation and inefficiency in these markets (Dowd, 2014), potentially leading to bubbles (Dale et al., 2005). These results also support concerns over cryptocurrencies' long-term viability for portfolio diversification, as excessive volatility and lower liquidity diminish the diversification benefits. Finally, these results give investors, policymakers, and regulators practical insights. This paper proceeds as follows. Section 2 describes the data and descriptive statistics, Section 3 discusses the methodology, and the empirical results are part of Section 4. Finally, Section 5 sets forth our conclusions.

2. Data and descriptive statistics

The source of news sentiment data on the COVID-19 panic, media hype, fake news, infodemic, sentiment, and media coverage index are from the Ravenpack database, which offers real-time media analytics, exploring announcements linked to the COVID-19 pandemic.[4] Our sample covers the period from January 1, 2020 to April 15, 2021. The sample start date coincides with the introduction of news sentiment indices related to the COVID-19 by Ravenpack. Prices are taken for the top 30 cryptocurrencies by market capitalisation from CoinMarketCap (https://coinmarketcap.com). Table 1 presents a short description of cryptocurrencies. The estimation of daily cryptocurrency returns is as follows: $r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) * 100$, where $r_{i,t}$ is cryptocurrency return i at day t; and $P_{i,t}$ and $P_{i,t-1}$ are prices at day t and $t-1$, respectively. Table 2 presents descriptive statistics. Results demonstrate that the average return (median) for all the currencies is positive, and cryptocurrencies increased their valuation over the study period. The mean values are near zero for USDT and DAI. DAI is the least volatile cryptocurrency of the set, while DOGE is the most (although it does not allow the highest average return, which RUNE gave). Most cryptocurrency returns exhibit either negative or positive skewness, indicating a greater likelihood of considerable price variation. However, almost all the cryptocurrencies (20 in 30) showed a negative skew, meaning negative returns are more frequent than positive ones. The returns are leptokurtic and distinctively non-Gaussian. The rejection of the Jarque–Bera test lends support at the 1%

[4] Table A1 in the appendix provides the definition of the Ravenpack indexes on the COVID-19 pandemic.

Table 2
Descriptive statistics, January 1, 2020–April 15, 2021.

Cryptos	Mean	Median	Stdev	Skewness	Kurtosis	ADF test	PP test
BTC	0.4657	0.2999	4.1236	−2.8553	36.4047	−7.6261***	−22.8540***
ETH	0.6299	0.6411	5.3881	−2.3175	25.1589	−7.6261***	−22.8540***
BNB	0.4282	0.7806	6.4425	0.1183	21.3872	−7.2228***	−23.5020***
XRP	0.4760	0.2536	7.0978	0.0560	16.8048	−7.8251***	−23.6020***
USDT	0.0001	0.0000	0.5066	0.1668	42.6054	−12.6780***	−47.2190***
DOGE	0.9550	0.0687	10.4249	7.0499	96.0943	−7.1074***	−20.8150***
ADA	0.8084	0.5980	6.3995	−0.5948	9.5555	−7.4485***	−23.9900***
BCH	0.3068	0.2976	5.9851	−1.6480	19.0209	−7.7515***	−23.6620***
LTC	0.4110	0.3326	5.4266	−1.2886	11.2663	−7.9719***	−23.1970***
LINK	0.6760	0.5305	6.9432	−1.3321	13.9770	−7.5428***	−23.5210***
VET	0.7467	0.4893	7.2907	−1.0998	11.6196	−7.4856***	−24.3100***
XLM	0.5035	0.4104	5.7931	0.5825	4.0205	−7.1054***	−23.0920***
THETA	1.0562	0.7070	7.5554	−0.7209	9.6662	−7.1387***	−23.8870***
TRX	0.5339	0.4091	5.9810	−0.9606	15.1603	−7.6996***	−23.6040***
XMR	0.4972	0.7031	4.6373	−0.0389	3.2028	−8.0769***	−25.0430***
LUNA	0.8871	0.0441	7.7686	2.0443	12.2603	−6.0358***	−23.2840***
EOS	0.2373	0.0000	5.7507	−1.4887	14.1100	−7.5987***	−23.7560***
MIOTA	0.5553	0.4726	6.4029	−0.9486	13.5693	−7.1828***	−23.4540***
CRO	0.4221	0.5938	5.7622	−0.8477	20.8193	−7.2775***	−23.8250***
BTT	0.7154	0.1353	7.4632	2.0165	28.0499	−7.3113***	−21.6060***
HT	0.4342	0.2120	5.4999	−0.0868	27.7893	−8.3462***	−25.0360***
XTZ	0.3435	0.3809	6.3650	−1.7636	17.9125	−7.5456***	−24.6590***
ETC	0.3930	0.3610	5.9775	−1.0310	14.4313	−6.4224***	−22.6370***
ALGO	0.4196	0.2798	7.2276	−1.3477	14.8941	−7.8868***	−22.6910***
DAI	0.0004	0.0000	1.1510	−0.5054	11.9009	−10.5170***	−48.3900***
RUNE	1.1314	0.5128	8.4061	−0.0714	1.9992	−7.7539***	−22.7610***
DASH	0.4403	0.3377	6.6058	0.6895	13.4843	−7.4976***	−22.2580***
CHZ	0.9183	0.2826	8.4353	0.8763	24.0266	−6.1304***	−21.1370***
XEM	0.5550	0.2808	6.6671	−0.4380	6.5745	−7.2193***	−23.1780***
STX	0.7088	0.1359	8.4846	0.7461	26.7971	−7.8474***	−25.6710***

Notes:
The augmented Dickey–Fuller (ADF) and Philip–Perron (PP) test used to check the unit root of return series.
***Significance at the 5%.

significant level,[5] consistent with the regular stylised fact of fat tails. The augmented Dickey–Fuller test (ADF) and Philip–Perron (PP) test demonstrate that cryptocurrency return series are stationary (see Table 2). The media coverage index rose sharply during the beginning of the pandemic and peaked in March, coinciding with the period when the World Health Organization (WHO) declared COVID-19 a pandemic.[6] The highest media coverage index, in March 2020, reflects that global financial markets witnessed sharp declines (Akhtaruzzaman et al., 2021a). Similarly, the panic, media hype, and infodemic indices peaked in March 2020.[7] Interestingly, many cryptocurrencies experienced jumps in volatility in March 2020 and February–March 2021. The higher volatility in March 2020 is due to the onset of the pandemic (Corbet et al., 2021). The latter episode of volatility in 2021 reflects a surge, partly attributed to statements made by Elon Musk (Hobbs, 2021). Moreover, the volatility pattern reflects that the markets react immediately to news related to COVID-19 developments, which linear models may fall short in capturing the behaviour. Further, to check the returns distribution pattern, we apply the BDS test of Broock et al. (1996) to examine spatial dependence and nonlinear structure. The results of the BDS test reveal the presence of nonlinearity in return series. Thus, the BDS test results substantiate the application of a nonlinear framework to test causal dependence (see Table 3).

3. Methodology

Analysis of causality holds great importance in studying financial market behaviour, and linear Granger causality is most commonly used to understand causal behaviour. However, attempts to understand behaviour and directional causality have motivated researchers to search for more efficient and global approaches (see, for example, Abdennadher and Hellara, 2018; Agbloyor et al., 2013; Comincioli, 1996; Stavroglou et al., 2019). However, the credit for testing causality goes to Granger (1969); the Granger causality test (GC) is one of the most popularly used in the financial literature to evaluate the bidirectional relationship between variables. GC assesses how past values of a given variable impact another variable in a vector autoregressive (VAR) framework, including past and present values of both variables.

Formally, a given variable Y Granger causes X, with lags k and l, if

$$F\left(x_t \middle| x_{t-1}^{(k)}, y_{t-1}^{(l)}\right) \neq F\left(x_t \middle| x_{t-1}^{(k)}\right), \tag{1}$$

meaning that the past values of Y can explain the present value of X, considering the past values of the variable. Similarly, it is possible to find whether X Granger causes Y, if

$$F\left(y_t \middle| x_{t-1}^{(k)}, y_{t-1}^{(l)}\right) \neq F\left(y_t \middle| y_{t-1}^{(l)}\right). \tag{2}$$

Granger causality is one of the best-known causality measures significantly used in major causality studies in the financial market. However, as it is a second-order statisitics, focusing on correlation-centred measure which has a severe limitation. It is limited to analysing the linear impact between variables, limiting its relevance to linear systems (Gencaga et al., 2015). As such, it may lead to a loss of information when the relationships between variables have nonlinear structures. Therefore, it is critical to use more global measures to capture both the linear and the nonlinear relationship between variables or between markets.

5 Figures A1 and A2 in the appendix present the price and return series, respectively, of the 30 cryptocurrencies.

6 Figure A3 in the appendix presents sentiment news indices by Ravenpack.

7 Figure A4 in the appendix presents the conditional volatility of cryptocurrency returns. Conditional volatility is estimated using a GARCH (1,1) model with a constant as the only regressor. We estimate the conditional volatility of cryptocurrency return using other GARCH models: GJR-GARCH (Glosten et al., 1993); EGARCH (Nelson, 1991); IGARCH (Engle and Bollerslev, 1986); APARCH (Ding et al., 1993) for our robustness check. We find similar conditional volatility of cryptocurrency return using these alternative GARCH models.

Table 3
BDS test results, January 1, 2020–April 15, 2021.

Cryptos	m	ε (1)	ε (2)	ε (3)	ε (4)
BTC	2	2.9444	2.8544	2.6355	2.1587
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	3.1339	2.4114	2.1990	1.9987
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
ETH	2	2.4558	2.5094	2.5302	2.4289
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	2.7203	2.8894	2.7510	2.7279
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
BNB	2	5.4762	6.9610	7.2520	7.1507
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	6.6441	7.9203	7.4799	6.8558
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
XRP	2	7.9473	6.2280	6.1843	5.3456
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	10.3679	7.7647	7.1115	6.3731
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
USDT	2	11.1999	10.6716	10.6391	8.3295
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	11.6899	11.0857	11.0759	8.4664
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DOGE	2	10.6368	9.0406	8.5708	7.8353
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	11.2474	9.2907	9.1241	8.2433
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
ADA	2	2.5430	3.3264	3.0314	2.4549
		(0.0001)	(0.0008)	(0.0024)	(0.0014)
	3	2.4869	3.2976	3.1062	2.6604
		(0.0002)	(0.0009)	(0.0018)	(0.0078)
BCH	2	5.5857	4.4405	2.6581	1.3245
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	5.2543	4.3471	3.0287	1.7869
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
LTC	2	3.5150	3.9805	3.1962	2.0667
		(0.0004)	(0.0000)	(0.0013)	(0.0038)
	3	3.4456	3.4398	2.9187	1.7721
		(0.0005)	(0.0000)	(0.0035)	(0.0076)
LINK	2	2.0084	2.5722	2.8375	2.5628
		(0.0004)	(0.0012)	(0.0045)	(0.0010)
	3	2.2614	2.9298	3.5832	3.2739
		(0.0002)	(0.0033)	(0.0030)	(0.0010)
VET	2	3.0629	2.7179	3.2055	3.6333
		(0.0002)	(0.0065)	(0.0013)	(0.0002)
	3	3.8079	3.4912	3.8690	3.8415
		(0.0001)	(0.0004)	(0.0001)	(0.0001)
XLM	2	4.8490	4.5723	4.5440	5.0854
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	5.8883	5.5943	5.3281	5.7661
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
THETA	2	3.9868	4.2423	3.7313	3.3431
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	4.5573	3.4912	4.4230	3.7923
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
TRX	2	6.1200	5.3054	4.2226	3.4537
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	7.9228	6.3764	5.0925	3.9047
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
XMR	2	4.5862	3.8254	3.1035	2.7417
		(0.0000)	(0.0001)	(0.0019)	(0.0006)
	3	4.1952	3.6294	2.6828	2.4519
		(0.0000)	(0.0002)	(0.0073)	(0.0011)
LUNA	2	4.5730	4.2742	4.3347	3.9288
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	7.8450	5.7269	4.8076	4.2964
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
EOS	2	4.2419	4.5851	5.0691	4.8544
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	5.4566	5.1855	5.2238	4.6803
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
MIOTA	2	2.2292	3.3372	4.2766	4.0858
		(0.0002)	(0.0000)	(0.0000)	(0.0000)
	3	3.0465	4.5497	5.7261	5.5685
		(0.0002)	(0.0000)	(0.0000)	(0.0000)
CRO	2	3.0030	3.5625	3.5455	4.2989
		(0.0020)	(0.0003)	(0.0000)	(0.0000)
	3	3.8226	4.5618	4.1952	4.3306
		(0.0001)	(0.0000)	(0.0003)	(0.0000)
BTT	2	5.7594	4.2001	3.5203	3.1646
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	7.0120	5.1449	4.4588	4.2519
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
HT	2	8.8155	7.7846	8.4584	8.4622
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	9.7909	8.1637	8.4173	8.7302
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
XTZ	2	3.6261	3.7040	3.5781	3.4627
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	4.5142	4.5377	4.5720	3.9142
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
ETC	2	5.8804	4.9576	4.4929	4.3038
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	7.2440	5.7141	4.8466	3.9393
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
ALGO	2	2.2928	2.4566	2.0716	2.4315
		(0.0002)	(0.0000)	(0.0020)	(0.0004)
	3	2.7630	2.4352	2.4203	2.4306
		(0.0001)	(0.0000)	(0.0012)	(0.0005)
DAI	2	8.7258	8.3196	9.7448	10.1192
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	15.1222	11.3237	11.5154	11.4856
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
RUNE	2	3.2956	2.8392	2.5374	1.9622
		(0.0009)	(0.0040)	(0.0011)	(0.0049)
	3	3.3511	3.3151	3.2717	2.7881
		(0.0008)	(0.0009)	(0.0001)	(0.0053)
DASH	2	5.3407	5.4767	5.8032	4.7984
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	5.8277	6.1344	6.3439	5.1384
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
CHZ	2	7.7515	7.9099	7.0493	6.8442
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	9.4837	8.7427	7.7078	7.0862
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
XEM	2	6.6542	5.7325	4.2819	3.0915
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	8.2862	6.7722	5.1389	3.2580
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
STX	2	2.2920	2.1225	2.2529	2.2573
		(0.0021)	(0.0033)	(0.0024)	(0.0000)
	3	3.9890	4.3345	4.2216	3.5092
		(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: The entries are the BDS test (Broock et al., 1996) statistics, and p-values are within brackets. The parameter m is the embedding dimension, and ε is the epsilon values for close points.

Contrary to GC, information-theory-based measures, such as mutual information (MI) or transfer entropy (TE), consider the whole structure of time series (Darbellay and Wuertz, 2000), allowing to measure both linear and nonlinear dependencies between two-time series. MI is a bivariate measure based on the Shannon (1948) entropy as MI absolute values are not limited upwards, which makes MI an imperfect measure of dependence (Granger et al., 2004). It measures only mutual dependence allowing for quantifying the information shared between two random variables (Fiedor, 2014) or between two-time series. MI aids in inferring the amount of information about one random variable through the observation of another random one. However, it does not indicate causality direction between variables (Ferreira et al., 2017) and fails to measure or quantify the flow of information (Jizba et al., 2012), hence demands an asymmetric measure to quantify and measure the information flow in a finance context (Dimpfl and Peter, 2014). Schreiber (2000) introduced a dynamic structure to mutual information by considering transition probabilities. He coupled the Shannon (1948) entropy and the Kullback and Leibler (1951) distance concepts and proposed a measure that allows for the above-referred assessment, the TE. TE not only allows to capture and measure of both linear and nonlinear relationships, but it also measures information flow from one random variable (or time-series) to another. Thus, the information flow from Y to X is given by

$$TE_{Y\to X}(k,l)=\sum_{x,y}p\left(x_{t+1},x_t^{(k)},y_t^{(l)}\right)\log\frac{p\left(x_{t+1}\middle|x_t^{(k)},y_t^{(l)}\right)}{p\left(x_{t+1}\middle|x_t^{(k)}\right)} \tag{3}$$

Eq. (3) is an asymmetric directional measure of the dependence and relation between variables. It measures the information flow from Y to X, quantifying the additional information about the future value of X gained by observing past values of Y. It can distinguish driving and responding elements and detect asymmetry in the interaction of time series. Thus, TE considers only the dependency is originating in source series Y, not considering dependences caused by common external sources. Analogously, used to calculate the information flow in the opposite direction, i.e., $TE_{X\to Y}(l,k)$. Thus, considering the difference between TEs helps find the dominant direction of information flow between pairs of variables (Behrendt et al., 2019). In contrast, the Granger causality or other tests identifies a source's interventions that affect the target variable. TE focuses on whether observations of the source can help predict state transitions making TE a dynamic and directional measure of predictive information (generally meant to reduce uncertainty). Instead of being only a measure identifying the causal information flow (Caţaron and Andonie, 2018; Moldovan et al., 2020). Though similarities exist between Granger causality and TE, TE is an information-theoretic measure and model-free approach not limited to linearity and normality restrictions on data behaviour. Hence it is helpful for an in-depth evaluation of the complex behaviour of cryptocurrencies, unravelling the existence of relationships between variables and their respective magnitude and direction (Barnett et al., 2009).

Estimating TE is done by considering the dependence on the discretisation of space and the possible relevance of tails in the distributions (e.g., Jizba et al., 2012). To test the significance of TE estimations, we use the bootstrap method proposed by Dimpfl and Peter (2013), which employs 300 replications to obtain the estimated distribution for testing the null hypothesis of the absence of information flow. TE has been used in extant literature to study financial markets (see, e.g., Baek et al., 2005; Dimpfl and Peter, 2013; Kim et al., 2020; Osei and Adam, 2020). In addition to TE, we estimate net TE, given by $NET\ TE_{Y\to X} = TE_{Y\to X} - TE_{X\to Y}$ identifying which of the variables in each pair is a net influencer or is net influenced. As in causality analysis, it is important to determine the direction of causality. In a two-way relation between X and Y variables, causality direction is assessed throughout the dominant direction of information flow between pairs of variables (Behrendt et al., 2019). The difference between both TEs (i.e., $TE_{Y\to X}(k,l)$ and $TE_{X\to Y}(k,l)$) defined by He and Shang (2017) as net TE (*NetTE*), $NetTE_{X,Y}(k,l)$, allows assessment of the referred dominant direction of information flow. The *NetTE* between X and Y variables is given by:

$$NetTE_{Y\to X}(k,l)=TE_{Y\to X}(k,l)-TE_{X\to Y}(k,l). \tag{4}$$

In this context, a positive value for $NetTE_{Y\to X}(k,l)$ ($TE_{Y\to X}(k,l) - TE_{X\to Y}(k,l) > 0$) means that the *NetTE* is from Y to X, i.e., the dominant direction of information flow is from Y to X (Y influences X more than X influences Y). Similarly, if TE is negative, then X influences Y more than the other way around, whereas a negative value suggests ($TE_{Y\to X}(k,l) - TE_{X\to Y}(k,l) < 0$) the dominant direction of information flow is the opposite (from X to Y). Both nonzero values are associated with a degree of asymmetry in the interaction (Porfiri, 2018). $NetTE_{Y\to X}(k,l) = 0$ could mean that X and Y are independent ($T_{Y\to X}(k,l) = T_{X\to Y}(k,l) = 0$), or that there is no predominant direction of causality ($TE_{Y\to X}(k,l) > 0$ and $TE_{X\to Y}(k,l) > 0$) (Camacho et al., 2021). For this paper, we performed TE using open-source software in the R language. Compared to MI, TE is better adaptive to detect the direct exchange of information between two systems (Karkowska and Urjasz, 2022), justifying the application of TE for the current study.

4. Empirical results

To quantify the information flow between news sentiment indices related to the COVID–19 and the cryptocurrency returns, we applied TE. The results show that panic, media hype, fake news, infodemic, sentiment and the media coverage index of COVID-19 significantly affects cryptocurrencies (Corbet et al., 2020c; Gurdgiev and O'Loughlin, 2020). The influence of the media hype index is statistically significant in the majority of the 30 cryptocurrencies, precisely 23. The media hype index measures the percentage of news about the novel coronavirus; this index significantly influences BCH, DASH, USDT, and DAI. More than half of the 30 cryptocurrencies are statistically significant influence by news sentiment. News sentiment indices commonly affect BCH, DASH, XMR, USDT, and DAI. The panic index influences VET, and the media coverage index influences ADA and XEM. However, the panic and media coverage indices are different; the former measures the level of news chatter that references panic or hysteria caused by the pandemic, while the latter calculates the percentage of all news sources covering the novel coronavirus. In contrast, the infodemic index is related to all entities (such as places, companies, and organisations) reported in the media alongside COVID-19.

Note that the fake news index influences 13 cryptos including BTC, BCH, and XMR. Fake news is the only sentiment index that appears to affect BTC significantly. This evidence is not surprising as BTC is the first cryptocurrency launched and the most traded with the highest market capitalisation, a prima facie victim of fake news. On the other hand, sentiment shows statistically significant levels of influence in only 13 cryptocurrencies, with DAI standing out with a 1% significance level and USDT and LINK at a 5% significance level. Further, analysis indicates that all the sentiment news indices highly influence DAI at a 1% significance level; the only exception is the fake news index, with significance at 10%. The result is an exception as the DAI price is soft-pegged to the US dollar and collateralised by a mix of other cryptocurrencies.

In contrast, none of the indexes impacts DOGE. Moreover, the return series of BCH, XMR, DASH, USDT and DAI show greater levels of influence on the index used. Though coins and tokens differ in market capitalisation, the results indicate that sentiment indices influence the irrespective of the market capitalisation of cryptocurrencies, with our sample comprising 22 coins and eight tokens.[8] Given the TE results, it appears that the sentiment indices more influence token cryptocurrencies.

Further, Naeem et al. (2021) suggest that sentiments related to optimism/happiness are better predictors of cryptocurrency returns than fear sentiments. Our sentiment indices are related more to fear or panic; thus, our results provide a contrarian perspective. Our results indicate that fatalistic and sensationalist news released via the internet greatly influences cryptocurrencies. We check net TE to determine casualty direction, finding that news sentiment drives cryptocurrency returns. Keskin and

[8] Coins and tokens differ in their operational architecture. Coins have their own blockchains, while tokens do not.

Table 4
Results of impact of COVID-19 news on cryptocurrency returns using transfer entropy, January 1, 2020–April 15, 2021.

Cryptos	Panic	Media_ Hype	Fake	Sentiment	Infodemic	Media_ Coverage
BTC	0.0205*	0.0164*	0.0222**	0.0216*	0.0070	0.0136*
ETH	0.0137*	0.0078	0.0165*	0.0171*	0.0089	0.0069
BNB	0.0137*	0.0101*	0.0132	0.0148	0.0107*	0.0108*
XRP	0.0076	0.0107*	0.0087	0.0063	0.0068	0.0101*
USDT	0.0396***	0.0366***	0.0223*	0.0279**	0.0166**	0.0214***
DOGE	0.0091	0.0091	0.0085	0.0087	0.0091	0.0091
ADA	0.0092	0.0115*	0.0119	0.0039	0.0116*	0.0118**
BCH	0.0278**	0.0247***	0.0257***	0.0091	0.0243***	0.0225***
LTC	0.0133*	0.0114*	0.0079	0.0071	0.0085	0.0077
LINK	0.0195*	0.0087	0.0148	0.0210**	0.0112*	0.0074
VET	0.0129**	0.0108	0.0153*	0.0077	0.0107**	0.0106*
XLM	0.0145*	0.0096*	0.0093	0.0073	0.0086	0.0053
THETA	0.0123	0.0115*	0.0107	0.0078	0.0083	0.0106*
TRX	0.0075	0.0103*	0.0105	0.0103	0.0068	0.0103*
XMR	0.0260**	0.0192**	0.0335***	0.0164*	0.0207***	0.0208**
LUNA	0.0106	0.0100*	0.0149*	0.0102*	0.0132*	0.0128*
EOS	0.0093	0.0086	0.0083	0.0124*	0.0068	0.0054
MIOTA	0.0246**	0.0113*	0.0143*	0.0218*	0.0130*	0.0101*
CRO	0.0184*	0.0129*	0.0018	0.0101	0.0165*	0.0084
BTT	0.0111	0.0108*	0.0144*	0.0088	0.0112*	0.0115
HT	0.0118*	0.0119*	0.0141*	0.0098	0.0115*	0.0094
XTZ	0.0175*	0.0064	0.0128	0.0136*	0.0065	0.0093
ETC	0.0129	0.0124*	0.0120	0.0127*	0.0022	0.0110*
ALGO	0.0081	0.0118*	0.0118	0.0059	0.0126*	0.0082
DAI	0.0480***	0.0396***	0.0183*	0.0489***	0.0293***	0.0462***
RUNE	0.0099	0.0117	0.0153*	0.0107	0.0078	0.0106*
DASH	0.0271**	0.0219***	0.0228*	0.0191*	0.0235***	0.0237**
CHZ	0.0099	0.0125*	0.0097	0.0098	0.0104*	0.0091
XEM	0.0129	0.0157*	0.0129	0.0110	0.0122*	0.0157**
STX	0.0113	0.0173**	0.0111	0.0129*	0.0063	0.0078

*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

Table 5
Net transfer entropy values, January 1, 2020–April 15, 2021.

Cryptos	Panic	Media Hype	Fake	Sentiment	Infodemic	Media Coverage
BTC	−0.0050	−0.0164	−0.0051	−0.0085	−0.0082	−0.0076
ETH	−0.0022	−0.0188	−0.0004	−0.0165	−0.0093	−0.0001
BNB	−0.0253	−0.0245	−0.0142	−0.0171	−0.0114	−0.0036
XRP	0.0045	−0.0039	−0.0002	−0.0003	−0.0032	−0.0079
USDT	−0.0253	−0.0245	−0.0142	−0.0171	−0.0114	−0.0036
DOGE	−0.0061	−0.0074	−0.0072	0.0009	−0.0056	−0.0070
ADA	−0.0024	−0.0047	−0.0013	−0.0031	−0.0023	−0.0009
BCH	−0.0022	−0.0203	−0.0188	0.0040	−0.0165	−0.0093
LTC	−0.0112	−0.0045	0.0036	0.0057	−0.0085	0.0077
LINK	−0.0119	−0.0057	−0.0061	−0.0033	−0.0059	−0.0040
VET	−0.0053	−0.0046	−0.0066	0.0091	−0.0082	−0.0010
XLM	−0.0053	−0.0110	−0.0021	−0.0001	−0.0019	−0.0017
THETA	−0.0020	−0.0085	0.0046	−0.0012	−0.0048	−0.0078
TRX	−0.0125	−0.0085	−0.0030	−0.0053	−0.0033	−0.0082
XMR	−0.0051	−0.0132	−0.0223	−0.0003	−0.0133	−0.0108
LUNA	−0.0064	−0.0032	−0.0086	−0.0072	−0.0078	−0.0106
EOS	0.0198	−0.0001	−0.0042	−0.0062	−0.0001	0.0065
MIOTA	−0.0076	−0.0100	−0.0071	−0.0032	−0.0104	−0.0010
CRO	−0.0094	−0.0078	−0.0105	0.0039	−0.0126	0.0004
BTT	0.0206	−0.0065	−0.0009	−0.0018	−0.0051	−0.0043
HT	−0.0100	−0.0024	−0.0063	−0.0036	−0.0054	−0.0030
XTZ	−0.0056	0.0020	−0.0018	−0.0041	−0.0008	0.0002
ETC	0.0280	−0.0044	0.0015	−0.0034	0.0035	−0.0098
ALGO	0.0250	−0.0034	−0.0058	0.0011	−0.0035	0.0040
DAI	−0.0027	−0.0202	−0.0138	−0.0300	−0.0155	−0.0330
RUNE	−0.0002	−0.0013	−0.0053	0.0032	−0.0012	−0.0082
DASH	−0.0008	−0.0164	−0.0058	−0.0115	−0.0168	−0.0157
CHZ	0.0110	−0.0047	−0.0043	0.0030	−0.0043	−0.0027
XEM	0.0143	−0.0014	0.0145	−0.0063	−0.0038	−0.0010
STX	−0.0103	−0.0093	−0.0003	−0.0063	−0.0008	−0.0011

Notes: Net transfer entropy ($NetTE_{X,Y}(k,l)$) is estimated based on the Eq. (4). A positive *NetTE* indicates the direction of information flow is from *Y* to *X* and if the value is negative the information flow is in the opposite direction i.e., from *X to Y*. In Table 5, *X* is the news proxy and *Y* is cryptocurrency return.

Aste (2020) detect statistical causality between social sentiment changes and cryptocurrency returns, reporting a significant non-linear causal relationship in BTC, LTC, and XRP in both directions (from sentiments to returns and from returns to sentiments). In contrast to BTC, for LTC and XRP, net information transfer is in the direction of sentiment to returns. The findings support the study results of Anamika and Subramaniam (2022), who have asserted that news sentiment significantly impacts cryptocurrency returns (see Table 4).

Contrary to Keskin and Aste's (2020) findings, but in line with Anamika and Subramaniam (2022) the present study finds a unidirectional flow of information from sentiments to returns during the COVID−19 period. We adopt the nonlinear causality test of Kwon and Oh (2012) and Výrost et al. (2015). The test results indicate unidirectional causality from COVID−19 news sentiment to cryptocurrency returns. The diverse and heterogeneous nature of the various cryptocurrencies causes each to respond differently to the sentiment, further validating our results' robustness (see Table 5). [9]

5. Conclusion

This study explores the impact of six COVID-19 news sentiment indices on the market returns of the top 30 cryptocurrencies by market capitalisation. We check how news about the intensity of the pandemic affects the returns of these cryptocurrencies using the nonlinear technique of TE. Results reveal that the association between COVID-19 news sentiment and cryptocurrency returns is nonlinear, thus supporting Bouri et al. (2018) findings. Moreover, most of the cryptocurrencies had positive gains during COVID periods, indicating the ability to absorb news shocks and react during pandemic conditions. These results are noteworthy from the angle of portfolio diversification, showing the anchoring of cryptocurrencies to news sentiment. The results of our study indicate that the benefits of using cryptocurrencies can diminish because prices reflect excessive volatility in the pandemic period, consistent with previous findings (Cheah and Fry, 2015). This study shows that, contrary to expectations, cryptocurrencies are highly vulnerable to news content, especially media hype news. The cryptocurrency valuation is far from being realistic, and caution must be exercised while using cryptos for diversification. Besides, the cryptocurrency shares at least one stylised fact common to other markets: vulnerability to speculative bubbles impairing its hedging abilities. Thus, the present findings provide new insights on cryptocurrency markets to market participants, policymakers, and regulators. The current study has opened avenues for future research. Future studies should look into risk embeddedness in cryptos markets and how the riskiness has increased during the COVID-19 period bringing newer insights into how cryptos respond to a sudden surge in information signals.

CRediT authorship contribution statement

Ameet Kumar Banerjee: Concept, Design, Analysis, Writing, or revision of the manuscript. **Md Akhtaruzzaman:** Concept, Design, Analysis, Writing, or revision of the manuscript. **Andreia Dionisio:** Concept, Design, Analysis, Writing, or revision of the manuscript. **Dora Almeida:** Concept, Design, Analysis, Writing, or revision of the manuscript. **Ahmet Sensoy:** Concept, Design, Analysis, Writing, or revision of the manuscript.

[9] The results are available upon request.

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Appendix A. Supplementary data

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