



Information sharing among cryptocurrencies: Evidence from mutual information and approximate entropy during COVID-19

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ABSTRACT

In this paper, we use mutual information approach to investigate the information sharing between cryptocurrencies during the COVID-19 crisis. We also use the approximate entropy to study their dynamics before COVID-19 and during the pandemic. Results from the mutual information measure indicate a rise in information sharing and ordering in the cryptocurrency markets in the pandemic period, while the evidence from the approximate entropy estimates indicates a rise in randomness during the COVID-19 period. Our results provide new insights on the information sharing of cryptocurrencies and their reaction to shocks such as the COVID-19 pandemic.

1. Introduction

The COVID-19, which has started in December 2020, is a serious global health threat and authorities implement several restrictions ranging from enforcement of mask-wearing to total lockdowns. The efforts to stop the spread of the virus, lack of the vaccine, and asymptomatic transmission almost halt the economic systems. And the pandemic affects the global financial markets, economies, and all humanity. The outbreak of COVID-19 has attracted the overwhelming attention of researchers. The fast-emerging studies examine the impact of a pandemic on stock returns (Baker et al., 2020), volatility (Zaremba et al., 2020; Baek et al., 2020), and other asset classes such as gold, cryptocurrencies, oil prices, and real estate (Ling et al., 2020; Cheema et al., 2020; Demir et al., 2020a). A stream of this literature investigates whether cryptocurrencies, mainly Bitcoin, can serve as a hedge against the pandemic. According to Conlon and Mcgee (2020) and Conlon et al. (2020), Bitcoin cannot serve as a safe haven, instead, the inclusion of Bitcoin in the portfolio rises the downside risk. Ji et al. (2020) document that the safe-haven asset to equity indices' role of Bitcoin becomes less effective during the pandemic. However, Demir et al. (2020a) and Goodell and Goutte (2020) show COVID-19 leads to a rise in Bitcoin prices, especially in the later stages. Dutta et al. (2020) show that Bitcoin can be considered as only a diversifier in the pandemic period.

The cryptocurrency literature devotes a rising effort to examine the interrelationship between Bitcoin and other cryptocurrencies (Yi et al., 2018; Ciaian et al., 2018; Corbet et al., 2018; Ji et al., 2019; Katsiampa, 2019a, 2019b). Those studies, in general, show that there are interdependencies between Bitcoin and other cryptocurrencies however, the magnitude, direction, and timing of the relationship differ based on the data set, data period, and methodology. Yaya et al. (2019) and Demir et al. (2020b) consider how the relationship between cryptocurrencies change after the 2017 cryptocurrency market crash. Yaya et al. (2019) show that there is

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weaker cointegration in the post-crash period while Demir et al. (2020b) show that the asymmetric impact of Bitcoin on altcoins exists especially after the 2017 cryptocurrency price crash. Those studies document that a shock to the cryptocurrency market is likely to affect the relationship between cryptocurrencies.

With the outbreak of the COVID-19, recent literature explores whether the interrelationships across cryptocurrencies are affected by the pandemic. Bouri et al. (2021) argue that connectedness in the lower and upper tails are higher than those in the median of the conditional distribution implying the instability of the connectedness system during extreme events such as the outbreak of the COVID-19. Aslanidis et al. (2021) show that there is a tighter relationship among cryptocurrencies in the pandemic period. Likewise, Demiralay and Golitsis (2021) document that co-movements across cryptocurrencies increase substantially in the wake of COVID-19 implying that cryptocurrencies recoupled in the pandemic period. By using 19 cryptocurrencies, Shahzad et al. (2021) present that the spillover index intensifies after the outbreak of COVID-19. Finally, Lucey et al. (2021) argue that cryptocurrencies can be susceptible to different types of uncertainty, with the impact uncertainty being time-varying and changing due to an increased institutional interest in these assets.

While those studies focus on the connectedness across cryptocurrencies, we focus on the change of information sharing in the cryptocurrency market using the mutual information concept, a measure that studies the mutual dependence between random variables. Developing financial stock networks based on mutual information is relatively at an early stage (Kwon and Yang, 2008), yet, some studies use mutual information to study dependence among financial assets (Guo et al., 2018; Barbi and Pratavia, 2019; Khojine and Han, 2019).

However, to our knowledge, there is no yet study analyzing the cryptocurrency markets before and during the COVID-19 pandemic by estimating the mutual information among the different cryptocurrencies and estimating the approximate entropy of each. Mutual information is an entropy function that is the expected information level within a variable and it quantifies how one series behavior reflects the other one (Benedetto et al., 2019). Higher (lower) values of the mutual information measure indicate a stronger (weaker) dependency between two variables. Interdependencies among cryptocurrencies or in general financial variables are important to analyze potential financial exposures and the overall dynamics of the financial system risk (Bouri et al., 2021). This provides implications for investors in terms of risk management, portfolio diversification, and trading and hedging strategies.¹ Especially during a global health shock, understanding whether information sharing and regularity in the cryptocurrency market have been an important research question.

Previous studies use the correlation coefficients and copula methods for measuring financial dependency among financial assets returns (Bartram and Wang (2005), and Li and Zhu (2014)). However, the correlation coefficient measures only the linear correlation and cannot capture nonlinear dependence commonly observed in financial time series [Anagnostidis and Emmanouilides (2015)]. Correlation coefficients can only detect the monotonic functional dependence [Kojadinovic 2004], and in the case of the copula, one needs to select certain copula functions before adopting it as a method of measuring dependence. Compared with these methods, Mutual Information will have the following advantages: it measures both linear and nonlinear dependence; does not make any assumption on the underlying relationship of the variables, making it completely data-driven; and it is robust to noise (see, for example, Dionisio et al. (2004); Kinney and Atwal (2014); Hong and Kim (2011); and Ponta and Carbone (2018)).

A complimentary measure related to information theory is the concept of approximate entropy (*ApEn*) introduced by Pincus (1991). The objective of using approximate entropy along the mutual information is to assess the degree of regularity in a time series by extracting the noises from the original data and estimating its randomness. Given that entropy quantifies the amount of information, it is also a measure of the degree of randomness in the system.

In this paper, we explore the information sharing among the different cryptocurrencies and the stability and regularity of these assets. We find that both information sharing as represented by mutual information, and regularity as measured by the approximate entropy estimates, have been changing during the pandemic period for these cryptocurrencies. Specifically, by applying the mutual information concept, we find that information is changing between the Pre-COVID and the COVID periods. Specifically, for the pre-pandemic period, we find that Ethereum to be the dominant cryptocurrency in information sharing with Ripple, Bitcoin Cash, and Litecoin. Then Bitcoin is ranked second by having high information sharing with Ethereum, Ripple, Bitcoin Cash, and Litecoin. Comparing to the COVID-19 period, we notice a large change in information sharing among the eight pairs, with the highest between Ethereum and Ripple, Litecoin and Ripple, and Litecoin and Bitcoin Cash. Our results support those obtained by Aslanidis et al. (2021), Demiralay and Golitsis (2021), and Shahzad et al. (2021) indicating a substantial increase of co-movements across cryptocurrencies in the wake of COVID-19.

Our results from the approximate entropy also reveal less stability and higher irregularity during the pandemic period. The estimates of approximate entropy have increased during the COVID-19 period for our sample. An indication that cryptocurrencies are becoming riskier and less predictable. Our results fall in line with those obtained by Lahmiri and Bekiros (2020) who found that the mean of *ApEn* for the pre-COVID-19 period is smaller than the mean of those during the COVID-19 pandemic, indicating an augmented level of irregularity in the cryptocurrency markets. Yet, our findings from approximate entropy differ from those obtained by Mnif

¹ The traditional Markowitz model for portfolio selection uses the variance of the portfolio as a quantifier of the risk associated with the portfolio and tries to minimize it, while at the same time attaining required return from the portfolio. This method works well under the assumption of a linear relation amongst different assets. To overcome this issue, Philippatos and Wilson (1972) gave an entropy-based model which minimizes the entropy of the portfolio and maximizes the rate of return. Since then many researchers have proposed different models based on entropy to get a diversified portfolio, which is less risky, and at the same time give good returns (see for example Zhou et al. (2013); Pozzi et al. (2013); Sandoval Junior (2017); and Sharma and Habib (2019)).

et al. (2020) who found that cryptocurrencies have become more efficient during the pandemic period.

The rest of the paper is organized as follows. Section 2 explains the methodology and data set of the study. In section 3, we present and discuss the findings. The last section concludes the paper.

2. Empirical methodology and data

2.1. Information theory

Mutual information (MI) measures the mutual dependence (or how much information is communicated) between two random variables (i.e., Fraser and Swinney (1986); Cover and Thomas (2006); and Hutter (2001)). Specifically, MI represents the amount of information inferred about one random time series through observing another random one. It measures both linear and nonlinear dependencies between two time-series and can be seen as a non-linear equivalent of the correlation function (see, for example, Fraser and Swinney (1986) and Hoyer et al. (2005)). The concept of mutual information is linked to the entropy of a random variable. Entropy, $\tilde{E}$, is a measure of the amount of uncertainty associated with a variable X when no other information is available.² It is defined as:

$$\tilde{E}(X) \equiv E \left[\log \left(\frac{1}{p(x)} \right) \right] = - \sum_{x \in X} p(x) \log(p(x)) \quad (1)$$

where E denotes the “expected value”, and $p(x)$ represents the marginal probability density function of X . It is noted that, when the distribution of X is more uniform, uncertainty increases due to the lack of anticipation regarding the outcome of X . On the other hand, since $\log \left(\frac{1}{p(x)} \right)$ is synonymous with “information”, a higher entropy is associated with lesser information and thus a higher uncertainty.

To generalize the concept to the bivariate case, we consider two random variables X and Y , and denote $p(x)$, $q(y)$ to represent the marginal probability density functions of X and Y respectively, while $w(x, y)$ represents their joint probability density function. Then, the *Conditional Entropy* measuring the total amount of information contained in X given our knowledge on Y is defined as:

$$\tilde{E}(X|Y) = \sum_{x \in X} \sum_{y \in Y} w(x, y) \log \frac{q(y)}{w(x, y)} \quad (2)$$

The *Joint Entropy* between X and Y , is defined as:

$$\tilde{E}(X, Y) = \sum_{x \in X} \sum_{y \in Y} w(x, y) \log \frac{1}{w(x, y)} \quad (3)$$

Using the chain rule for the entropy, these measures are related through the following equation:

$$\tilde{E}(X, Y) = \tilde{E}(Y) + \tilde{E}(X|Y) \quad (4)$$

The *Mutual Information* between them $I(x; y)$, is defined as (Cover and Thomas, 2012):

$$I(x; y) = \sum_{x \in X} \sum_{y \in Y} w(x, y) \log \frac{w(x, y)}{p(x)q(y)} = \tilde{E}(X) - \tilde{E}(X|Y) \quad (5)$$

The positive symmetrical measure $I(x; y)$ defines the decrease in uncertainty about X given the information on Y . Higher (lower) values of the mutual information measure indicate a stronger (weaker) dependency between the variables X and Y . When the two variables are independent, the mutual information value is zero.

2.2. The approximate entropy

Another measure that is related to information theory is the concept of entropy, a measure that allows us to assess the amount of information mathematically. Researchers proposed different approaches to determine the appropriate entropy to classify chaotic systems. Some measures are useful for deterministic processes, yet using entropy techniques for finite, noisy, and stochastically derived time series is not advisable (Delgado and Bonal, 2019). When a signal contains random noise, the information carried by the signal dwindles. To overcome these limitations and analyze such signals, the approximate entropy (*ApEn*) introduced by Pincus (1991) can be utilized. It is proposed to measure correlation, persistent patterns, and assess the degree of irregularity or randomness in a time series of length N by extracting the noises from the original data. The approximate entropy (*ApEn*) is based on the work of Grassberger and Procaccia (1983) and can be explained by estimating its values: smaller *ApEn*-values is an indication of a greater chance that a set of

² Given its importance in information theory, entropy has been used in fields such as econophysics (Lahmiri et.al. (2020), Lahmiri et.al. (2017)), forecasting stock prices and blockchain evaluation (Karaca et.al. (2020) and Tang et.al. (2019)). Mutual Information has been also used in various studies to examine dependence structures or global correlation (Darbellay and Wuertz 2000; Menezes et al. 2012; and Ferreira and Dionísio 2014).

data will be followed by similar data, implying a greater regularity and less randomness. While a greater value for $ApEn$ indicates more irregularity and signifies randomness (see Pincus (1991); Pincus and Keefe (1992); and Pincus and Huang (1992)).

To calculate the $ApEn$, consider a series of data points $u(i)$ from $i = 1$ to N , and define the vector sequences $x(i)$ of a length m as follows:

$$x(i) = (u[i], u[i+1], \dots, u[i+m-1]) \quad (6)$$

Using a tolerance factor r , the distance $d(x[i], x[j])$ can be represented as the maximum difference between $x(i)$ and $x(j)$. Then, we can obtain the correlation sum of vector $x(i)$ as:

$$C_i^m = \frac{[\text{number of } j \text{ such that } d(x[i], x[j]) \leq r]}{(N - m + 1)} \quad (7)$$

where $j \leq (N - m + 1)$.

Given r , the $C_i^m(r)$ measures the regularity of patterns similar to a given one of window length m . $C_i^m(r)$ measures the summed correlation of vector $x(i)$ with all other vectors. Then, taking the natural logarithm of $C_i^m(r)$, the mean logarithmic correlation sum can be obtained as:

$$\Phi^m(r) = \sum_i \ln C_i^m(r) / (N - m + 1) \quad (8)$$

where $\sum_i$ is a sum from $i = 1$ to $(N - m + 1)$. $\Phi^m(r)$ measures the prevalence of repetitive patterns of length m within r . Then $\Phi^m(r)$ will be the average frequency of all the m -point patterns in the sequence. Finally, $ApEn(m, r, N)$ can be defined as:

$$ApEn(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \quad (9)$$

In this case, $ApEn$ measures the unpredictability of fluctuations in a time series. A large value of $ApEn$ indicates irregularity and unpredictability, while a low value of $ApEn$ indicates more predictability.³

2.3. Data

To study the impact of the COVID-19 pandemic on the mutual information among cryptocurrencies and stability of the cryptocurrency markets, we collect data on the most capitalized cryptocurrencies for the period April 20, 2019, until September 12, 2020. We consider two time periods: The pre-COVID-19 period runs from April 20, 2019, to December 31, 2019, and the during-COVID-19 period from January 1, 2020, to September 12, 2020.⁴ This gives us 256 trading days in the pandemic and pre-pandemic periods. We collect data for the following cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH), Binance Coin (BNB), ChainLink (LINK), Crypto (CRO), and Litecoin.⁵ We conduct our analysis using the continuously compounded return series.

4. Empirical results

Fig. 1 presents the time series behavior of the different cryptocurrencies and then Table 1 provides the statistical measures for the whole period, the pre-COVID-19 and the COVID-19 period. For the whole period, the majority of cryptocurrencies have a positive mean, except for Ripple and Bitcoin Cash. The most volatile currencies are Bitcoin Cash, LINK, and Crypto as represented by the standard deviation. All the series also show negative skewness and positive kurtosis, indicating deviation from normality. For the pre-COVID-19 period, ChainLink and Crypto are again the riskiest. Yet, for the majority of cryptocurrencies, their skewness becomes positive associated with positive kurtosis. However, for the during-COVID-19 period, Ethereum, Bitcoin Cash, Binance Coin, and LINK are the riskiest and then all the series show negative skewness as to the case of before the COVID-19 pandemic period.

The results from the mutual information (MI) estimations for the whole sample, pre-COVID-19 period, and the COVID-19 period are presented in Table 2. Values in each cell represent the mutual information transferred between each pair of cryptocurrencies. MI values range from 0 to 1 where 0 implies that two variables are independent and a value of 1 indicates maximum mutual information. In Table 3, we present the changes in the mutual information from the pre-COVID-19 period to the COVID-19 period. In this table, 1 (0) indicates that there is an increase (decrease) in mutual information in the related cryptocurrency pair in the COVID-19 period compared to the pre-COVID-19 period. According to Table 2, for the whole period, we notice the highest values of mutual information between Bitcoin and Ethereum, Ripple and Ethereum, Bitcoin Cash, and those of Bitcoin, Ethereum and Ripple, and finally, between

³ Entropy has been used in risk management and portfolio optimization. For example, Mercurio et al. (2020) introduced the return-entropy portfolio optimization (REPO) measure as a risk tool in the area of portfolio optimization, while Yu et al. (2014) compared the mean-variance efficiency and portfolio risk measures incorporating different entropy measures.

⁴ In line with the literature, we consider the COVID-19 period starting from January 1, 2020. (Le et al. 2020; Iqbal et al. 2021)

⁵ Initially, we collect top 10 cryptocurrencies based on the market capitalization on 14.09.2020 from <https://www.coindesk.com/coindesk20>. We don't include Tether in the analysis as it is theoretically pegged to 1 USD. Polkadot ranks 5th however it is introduced at 2020-08-19, so there is no data availability

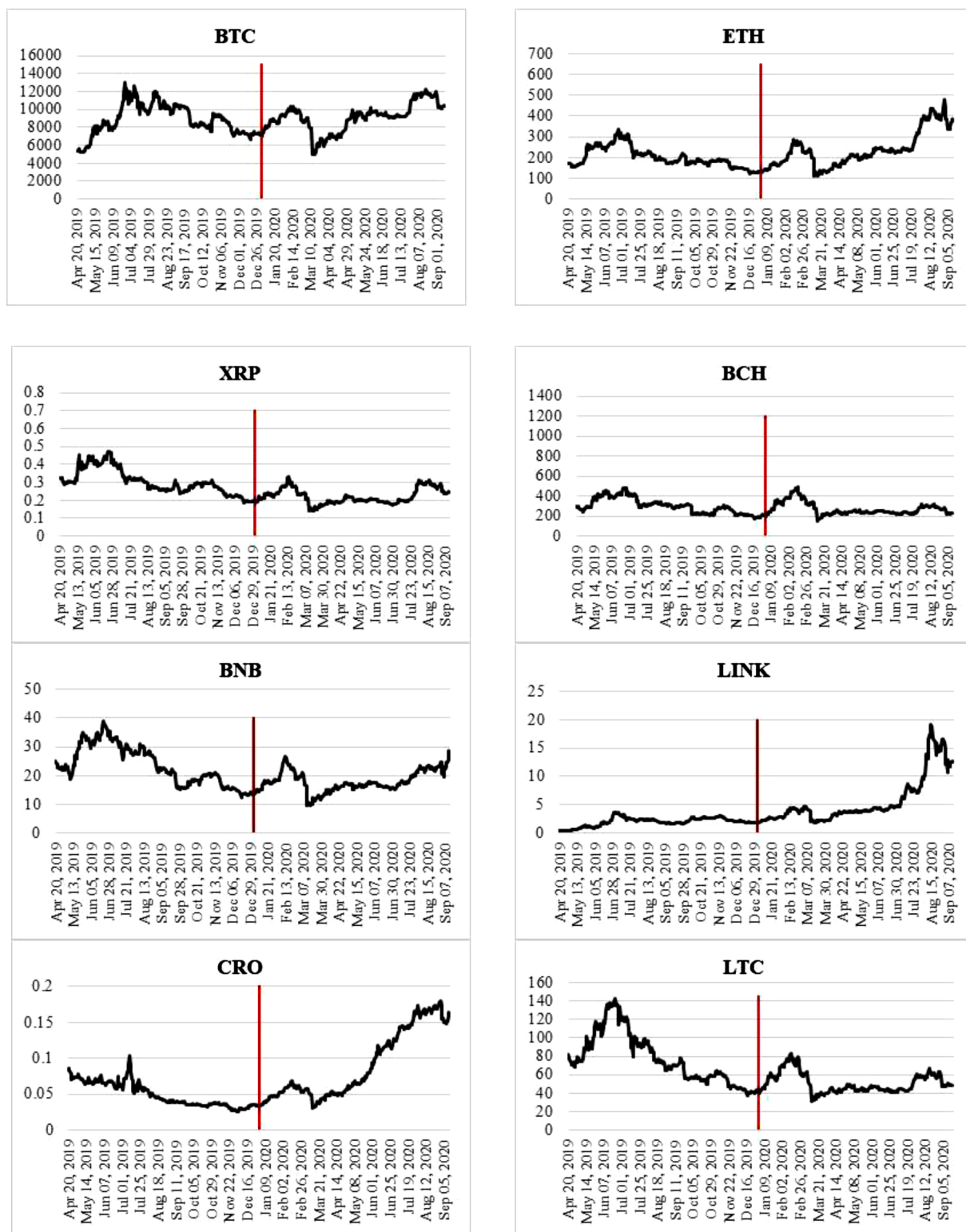


Fig. 1. The Price Graphs of Cryptocurrencies

Notes: The sample period is from April 20, 2019, until September 12, 2020. Returns are calculated based on the continuously compounded returns. Red vertical line indicates the start of the COVID-19.

Table 1
Descriptive Statistics.

Panel A - Whole Sample								
	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
Mean	0.0014	0.00156	−0.0005	−0.0005	0.00015	0.0059	0.00127	−0.0009
S.D.	0.0411	0.0498	0.0417	0.0549	0.0484	0.0699	0.050	0.0486
Maximum	0.167	0.173	0.228	0.269	0.193	0.484	0.257	0.191
Minimum	−0.464	−0.550	−0.398	−0.561	−0.542	−0.617	−0.490	−0.449
Skewness	−2.613	−2.705	−1.379	−1.966	−2.767	−0.382	−1.545	−1.488
Kurtosis	35.85	32.82	21.03	27.19	34.29	19.79	23.54	18.14
J.B.	23,801	6073	7158	12,920	21,714	6073	9279	5122
Panel B - Pre-COVID-19 Period								
	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
Mean	0.0011	−0.0011	−0.002	−0.0015	−0.0023	0.0049	−0.0036	−0.0025
S.D.	0.0038	0.0411	0.0387	0.0482	0.0399	0.0671	0.0521	0.044
Maximum	0.144	0.129	0.228	0.214	0.133	0.484	0.257	0.145
Minimum	−0.151	−0.183	−0.134	−0.276	−0.192	−0.215	−0.242	−0.180
Skewness	0.074	−0.613	0.505	−0.453	−0.114	1.918	0.598	0.056
Kurtosis	6.006	6.222	8.796	10.219	5.499	14.182	8.505	5.112
J.B.	96.67	126	369	564	67	1490	338	47
Panel C - The COVID-19 Period								
	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
Mean	0.0016	0.0042	0.0010	0.0005	0.0025	0.0069	0.0061	0.0006
S.D.	0.043	0.056	0.044	0.060	0.055	0.072	0.047	0.052
Maximum	0.167	0.173	0.142	0.269	0.193	0.237	0.141	0.191
Minimum	−0.464	−0.550	−0.398	−0.561	−0.542	−0.617	−0.490	−0.449
Skewness	−4.419	−3.431	−2.616	−2.680	−3.683	−2.179	−4.290	−2.616
Kurtosis	53.12	37.06	27.88	32.29	38.86	23.90	47.41	24.14
J.B.	28,169	13,128	7032	9646	14,579	4958	22,257	5109

Notes: The table provides the statistical measures of return of the cryptocurrencies for the whole sample, before COVID-19, and during the COVID-19 periods. The reported values are the Mean, Max (maximum), Min (minimum), S.D. (standard deviation), Skewness, and Kurtosis moments for each return distribution. J.B. is the Jarque-Bera (1980) test for normality with the significance in parenthesis. The sample period is from April 20, 2019, until September 12, 2020. Returns are calculated based on the continuously compounded returns.

Litecoin and those of Bitcoin, Ethereum, Ripple and Bitcoin Cash. For the whole period, Bitcoin, Ethereum, Ripple, Bitcoin Cash, and Litecoin seem to be the dominant cryptocurrencies in information sharing with Ripple and Litecoin having the highest values relatively.⁶

For the pre-pandemic period, Table 2 shows that Ethereum to be the dominant currency in information sharing with Ripple, Bitcoin Cash, and Litecoin. Then Bitcoin is ranked second by having high information sharing with Ethereum, Ripple, Bitcoin Cash, and Litecoin. Comparing those to the COVID-19 period, we notice a large change in information sharing among the eight pairs, with the highest between Ethereum and Ripple, Litecoin and Ripple, and Litecoin and Bitcoin Cash. Then Bitcoin information sharing comes second in its information sharing with Ethereum, Ripple, Bitcoin Cash, and Litecoin. Another noticeable observation is the rise of information sharing of Litecoin with the rest of cryptocurrencies. A finding that might suggest low potential diversification benefits opportunity between Litecoin and other cryptocurrencies, but some potential diversification benefits between Bitcoin Cash and Ripple.

Finally, Table 3 presents the changes in the information mutual sharing among our group, compared to the pre-COVID-19 period. Important observations during the Covid-19 period are explored. We observe that there is an increase in mutual information sharing in 26 pairs among 28 pairs. So, it implies that the mutual information has increased in the COVID-19 period. This is in line with the recent literature documenting that there are tighter relationships among cryptocurrencies in this period (Aslanidis et al., 2021; Demiralay and Golitsis, 2021). We also find that Bitcoin Cash shared less information with those of Ethereum and Ripple in the COVID-19 period compared to the pre-COVID-19 period. The reasons behind that can be related to the characteristics of Bitcoin Cash relative to other cryptocurrencies. Bitcoin Cash is not only a cryptocurrency but also a payment network. It was developed by bitcoin miners and developers concerned about the future of the cryptocurrency and its ability to scale. It has its blockchain and specifications. Further, it is well ahead of other cryptos in terms of transaction speed, lower average transaction fees, higher transaction rate per second, and Bitcoin Cash transfers data more quickly.

Different approaches have been proposed to estimate mutual information directly from samples in a non-parametric way, without ever describing the entire probability density. A popular estimator proposed by Kraskov et al. (2004) is the k-nearest-neighbor (kNN) based estimator. However, Gao et al. (2015) show that there are some undesired features of the kNN estimator, and suggest a new kNN estimator that needs significantly fewer samples for accurately estimating mutual information (we refer the reader to Gao et al. (2015) for more explanation). The new method is based on Kraskov et al. (2004) method, but adjusts for observed non-uniformity of the local

⁶ Mutual Information computation requires the entropy estimators. Our main results are based on the Empirical Estimator. As for the robustness check, we calculate the MI based on the different approaches namely Empirical Estimator, the Miller-Madow Correction Estimator, Shrink Estimator, and Schurman-Grassberger Estimator (see Meyer (2008) for more details). Our results are similar, and to save space, we are not reporting the results and are available upon request.

Table 2
Mutual Information Values.

Panel A - Whole Sample								
	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
BTC		0.577	0.481	0.537	0.377	0.206	0.264	0.485
ETH			0.626	0.589	0.438	0.277	0.231	0.615
XRP				0.568	0.357	0.242	0.189	0.620
BCH					0.424	0.246	0.189	0.614
BNB						0.246	0.173	0.391
LINK							0.086	0.240
CRO								0.238
LTC								
Panel B - Pre-COVID-19 period								
	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
BTC		0.494	0.407	0.452	0.318	0.132	0.109	0.418
ETH			0.549	0.575	0.337	0.224	0.116	0.541
XRP				0.547	0.284	0.181	0.095	0.450
BCH					0.367	0.213	0.102	0.484
BNB						0.135	0.111	0.304
LINK							0.021	0.127
CRO								0.130
LTC								
Panel C- The COVID-19 Period								
	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
BTC		0.585	0.535	0.537	0.379	0.247	0.455	0.560
ETH			0.603	0.529	0.493	0.330	0.329	0.589
XRP				0.539	0.401	0.249	0.392	0.664
BCH					0.404	0.243	0.357	0.678
BNB						0.233	0.231	0.428
LINK							0.185	0.283
CRO								0.347
LTC								

Notes: The table presents the mutual information estimations for the whole period, before-COVID-19 period and during COVID-19 period. Values represent the mutual information transferred between each pair of the cryptocurrencies. When MI is 0 the two variables are independent, while a value of 1 indicates maximum mutual information. The sample period is from April 20, 2019, until September 12, 2020. The pre-COVID-19 period runs from April 20, 2019, to December 31, 2019, and the during-COVID-19 period from January 1, 2020, to September 12, 2020.

Table 3
Changes in Mutual information.

	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
BTC		1	1	1	1	1	1	1
ETH			1	0	1	1	1	1
XRP				0	1	1	1	1
BCH					1	1	1	1
BNB						1	1	1
LINK							1	1
CRO								1
LTC								

Notes: 1 Indicates an increase and 0 a decrease.

neighborhood of each point in the sample. For robustness analysis, Table 4 provides the estimates of mutual information based on Gao et al. (2015) method for the Pre-Covid-19 and Covid-19 periods. It is observed that majority of estimates have increased during the pandemic period, confirming our results obtained from Table 3.

Then to assess the complexity patterns in the cryptocurrency markets before and during the COVID-19 period, we apply the approximate entropy $ApEn$ for the whole period, before-COVID-19 and the COVID-19 pandemic periods. The estimates are reported in Table 5. As can be seen, the estimates of approximate entropy for the whole period show a great deal of irregularity since most of the estimates are greater than one. However, the estimates are different for the pre-COVID-19 period and the COVID-19 pandemic period. As the results show that the estimates have increased during the COVID-19 period, an indication of more irregularity in the cryptocurrency times series dynamics. Interestingly, our results fall in line with those obtained by Lahmiri and Bekiros (2020) who found that the mean of $ApEn$ for the pre-COVID-19 period is smaller than the mean of those during the COVID-19 pandemic, indicating an augmented level of irregularity in the cryptocurrency markets. Yet, keep in mind that the sample data considered by Lahmiri and Bekiros (2020) is different from ours and the set of cryptocurrencies considered are not the same.

Finally, we map graphically the approximate entropy of our data set over a range of an embedding dimension of 2 and setting a filter factor to be 0.2 times the standard deviation of the data. Fig. 2 presents the results for the two periods: pre-COVID-19 and the COVID-19 pandemic. As can be seen from the graph, the approximate entropy behavior for all the cryptocurrencies quantifies an

Table 4

Mutual Information Values obtained by Local Non-Uniformity Corrected method of Gao, et. al (2015).

Panel A - Pre-COVID-19 period								
	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
BTC		0.723	0.549	0.511	0.275	0.110	0.064	0.503
ETH			0.702	0.684	0.335	0.219	0.060	0.701
XRP				0.558	0.256	0.195	0.008	0.537
BCH					0.298	0.151	0.055	0.575
BNB						0.101	0.036	0.401
LINK							0.005	0.173
CRO								0.038
LTC								
Panel B- The COVID-19 Period								
	BTC	ETH	XRP	BCH	BNB	LINK	CRO	LTC
BTC		0.673	0.616	0.627	0.544	0.268	0.490	0.736
ETH			0.763	0.690	0.655	0.362	0.345	0.798
XRP				0.681	0.560	0.289	0.365	0.823
BCH					0.553	0.282	0.348	0.890
BNB						0.285	0.293	0.525
LINK							0.125	0.376
CRO								0.414
LTC								

Notes: The table presents the mutual information estimations for the before-COVID-19 period and during COVID-19 period. Values represent the mutual information transferred between each pair of the cryptocurrencies. When MI is 0 the two variables are independent, while a value of 1 indicates maximum mutual information. The sample period is from April 20, 2019, until September 12, 2020. The pre-COVID-19 period runs from April 20, 2019, to December 31, 2019, and the during-COVID-19 period from January 1, 2020, to September 12, 2020.

Table 5

Approximate Entropy for the whole period, pre-COVID-19 and the COVID-19 period.

	Whole period	Before COVID-19	During COVID-19
BTC	1.317	1.065	1.157
ETH	1.361	1.041	1.062
XRP	1.282	1.030	1.120
BCH	1.359	1.078	1.156
BNB	1.350	1.027	1.149
LINK	1.385	1.081	1.091
CRO	1.287	1.007	1.167
LTC	1.339	1.008	1.168

Notes: The table provides the Approximate Entropy for the different cryptocurrencies for the whole period, before Covid-19 and during Covid-19 periods. The sample period is from April 20, 2019, until September 12, 2020. The pre-COVID-19 period runs from April 20, 2019, to December 31, 2019, and the during-COVID-19 period from January 1, 2020, to September 12, 2020.

augmented level of irregularity and unpredictability of fluctuations during the COVID-19 period, as all the cryptocurrencies show a higher level of estimates. The results confirm those obtained in Table 5 and indicate that the cryptocurrency time series are becoming more random and indicate lower levels of predictability. The findings of higher approximate entropy for the COVID-19 pandemic period are different than those obtained by Mnif et al. (2020) who found that cryptocurrencies have become more efficient during the pandemic period. Not a surprising result since we obtained similar evidence from the mutual information sharing, where the majority of our series had an increase in mutual information measures.

4. Conclusion and implications

The crisis of the COVID-19 pandemic has affected the global economy and caused major declines in many areas of world businesses. In this study, we attempt to study the information sharing among the different cryptocurrencies and the stability and regularity of these markets. We study the markets before and during the COVID-19 pandemic by estimating the mutual information among the different cryptocurrencies and estimating the approximate entropy of each.

We find that both information sharing as represented by mutual information, and regularity as measured by the approximate entropy estimates, have been changing during the pandemic period for these cryptocurrencies. Specifically, by applying the mutual information, and based on its estimates, we find that information is changing between the Pre-COVID and the COVID periods. This provides useful information-theoretic tools for analyzing the predictability of cryptocurrencies and how the markets incorporate information into the price system, having implications for the efficient market hypothesis. During crisis times, skilled investors may manipulate the price of cryptocurrencies, following “pump-and-dump” strategies by driving up demand to attract other investors, then drop their holdings once the price is high. This might be associated with a herding behavior; buying cryptocurrencies just because others are buying them.

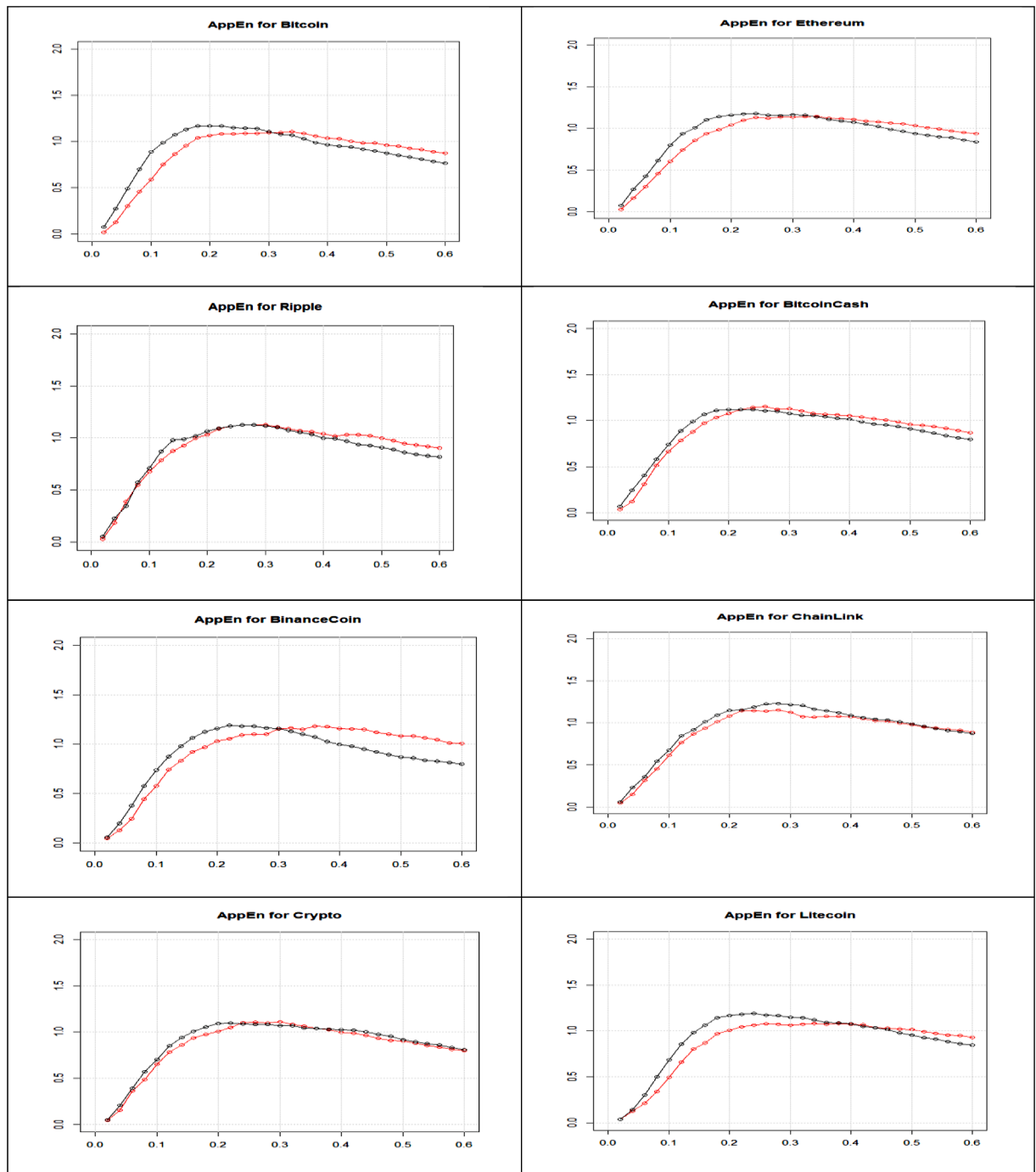


Fig. 2. The Approximate Entropy for the different cryptocurrencies.

Notes: The figure presents the Approximate Entropy for the different cryptocurrencies. The red line represents the Approximate Entropy for the before COVID-19 period. The black line represents the Approximate Entropy for the COVID-19 period. The sample period is from April 20, 2019, until September 12, 2020. The pre-COVID-19 period runs from April 20, 2019, to December 31, 2019, and the during-COVID-19 period from January 1, 2020, to September 12, 2020.

Our results also reveal less stability and higher irregularity during the pandemic compared to the pre-COVID-19 period, as measured by the approximated entropy results. An indication that cryptocurrencies are becoming riskier and less predictable. They often offer high returns and exhibit high volatility (Stosic et al., 2019). They are also often associated with contagion risk, bubbles, and financial instability (Bouri et al., 2019). Players in these markets are not homogeneous in their analytical capacity and risk tolerance;

and the rate at which information is incorporated and disseminated is not homogeneous, especially in crisis times (Lucey et al. (2021)).

The results obtained indicate that there is a possibility of profiting by exploring information contained in the cryptocurrency markets. In the cases where no formal controls inhibit the participation of investors and traders in these markets, such opportunities and inefficiencies would be short-lived and beneficial to investors and traders. Factors that characterize the cryptocurrency markets and information sharing among their returns, like illiquidity, asymmetries of information, poor regulation, or high transaction costs may be reasons underlying the relatively lower efficiency levels and the existence of profit opportunities.

Our findings can benefit investors and policymakers in making their investment decisions within the cryptocurrency markets (see for example Matkovskyy et al., 2021). The evidence of information transmission among cryptocurrencies over the two sub-periods is useful in making decisions in the areas of portfolio diversification, risk management, and trading and hedging strategies (Baur et al. (2018) and Bouri et al. (2020)). Yet, it is worth mentioning that cryptocurrencies are characterized by high volatility, lack the regulation and needed liquidity compared to conventional assets, and are not normally or elliptically distributed, which makes investors and traders pushed away from the uncertainty surrounding investment opportunities in these markets. Investors, in this case, should pay more attention to information flow between these assets, since the linear correlation used in portfolio construction involving cryptocurrencies may lead to misallocation of assets of the portfolio, exposing investors to high levels of risk.

Future research can explore the interdependencies among cryptocurrencies by using high-frequency data (Zhang et al. (2019)). Moreover, in the pandemic period, there are events such as the launch of Bakkt Bitcoin futures, halving, attempts to launch Libra, Ethereum 2.0 development, "Institutional" flows, Federal Reserve's efforts towards FedCoin which might affect the cryptocurrency market. Future studies can explore the impact of those specific events on the dependency among the different cryptocurrencies since they share information during extreme events. This would produce more specific evidence to guide improvements in terms of market microstructure embodied in the cryptocurrency markets.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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