Physica A 654 (2024) 130128

Contents lists available at ScienceDirect

Physica A: Statistical Mechanics and its Applications

journal homepage: www.elsevier.com/locate/physa

Crypto network

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ARTICLE INFO

JEL Classifications:
C32
G1

Keywords:
Cryptocurrencies
Digital Markets
Finance
Macroeconomics
Networks
Time Series Econometrics

ABSTRACT

The empirical literature has studied linkages in the cryptocurrency market because knowing how shocks pass from one currency to another helps policymakers and practitioners better counter their propagation in these and related markets. This paper contributes to this literature by proposing a methodology based on Granger causality and network analysis. Using the daily log-returns of 22 cryptocurrencies over the period 2018–2023, I develop a VAR model to infer unidirectional or bidirectional Granger causality among cryptocurrencies. These relationships are then transformed into a directed network and several centrality measures are calculated. The centrality measures are also observed over the years to understand the dynamics of the cryptocurrency network. I find out that each one unit increase in eigencentrality is associated with a 0.22 percent increase in log-returns. Cryptocurrencies are nontrivially connected, and in this sample Cardano, Dogecoin, Gridcoin, and Neo are amongst the most central in the network throughout the period. Some cryptocurrencies, such as Dogecoin or Neo, show decreasing centrality over the years, while others, such as Gridcoin, Litecoin, Namecoin, or Ripple, gain centrality. These results support the idea that the cryptocurrency market is no longer exclusively associated with Bitcoin and lay the groundwork for further study of shock propagation in financial markets.

1. Introduction

Cryptocurrencies are digital currencies whose transactions are managed by a decentralized system using cryptography, rather than by a centralized authority. Originally conceived as a secure means of payment, over the years cryptocurrencies have become an asset, mainly speculative in nature [2], and have entered the portfolios of many investors. The first cryptocurrency was Bitcoin, released as open-source software in 2009. As of June 2024, *Statista* reports that there were more than 10,000 other cryptocurrencies on the market.[1] Although cryptocurrencies are not considered currencies in the traditional sense, El Salvador was the first country in 2021 to pilot the use of Bitcoin as a legal tender to promote financial inclusion and job creation, and facilitate remittances [1]. The country launched Chivo Wallet, an application that offers many of the same benefits as a central bank digital currency, such as accessibility and the ability to pay peers and businesses and make deposits and withdrawals in both U.S. dollars (the country's official currency) and Bitcoin. Despite this innovative effort, research has documented a low and decreasing pattern of use of digital payments and Bitcoin in El Salvador [1].

An important peculiarity of the cryptocurrencies market is that it is always open. This means that shocks propagate very quickly and are very difficult to deal with. For this reason, the study of correlation in the cryptocurrency market has received increasing

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[1] https://www.statista.com/statistics/863917/number-crypto-coins-tokens/

https://doi.org/10.1016/j.physa.2024.130128
Received 21 June 2024; Received in revised form 5 August 2024; Accepted 24 September 2024
Available online 25 September 2024
0378-4371/

attention over the years.

Empirical literature has focused on both estimating the correlation between cryptocurrencies and building networks to study the links between them [15,16,23,4,5,8,9]. These works generally study a sample consisting of a couple of cryptocurrencies up to fifty and construct undirected networks based on correlation analysis. Other works have exploited the notion of Granger causality to find useful predictors to explain cryptocurrencies [25,3,10], while others have used the "direction" provided by Granger causality to derive directed networks for cryptocurrencies [12,13].

Knowing how shocks propagate in the cryptocurrency market is important, as researchers have found a significant contagion effect not only among cryptocurrencies, but also from cryptocurrencies to other markets, such as stocks or commodities [11,22]. Higher correlation in the cryptocurrency market is evidence of rapid shock propagation, but knowing how these shocks pass from one currency to another is also useful information, as it can enable policymakers and practitioners to better counter shock propagation, although the cryptocurrency market has proven to be resilient [7]. In this regard, deriving measures of centrality from such networks is useful for understanding which cryptocurrencies are most likely to propagate negative shocks and cause sequential failures in the network.

This work builds on this literature by using a methodology that allows us not only to construct directed networks, which are important for understanding how shocks can propagate from one cryptocurrency to another, but also to compute measures of centrality on these networks. This is achieved by estimating a vector autoregression (VAR) model with 22 equations, one for each of the cryptocurrencies in the sample. The estimated coefficients are then statistically tested to see which cryptocurrencies Granger cause the others. This allows us to determine the direction of the links between cryptocurrencies, which are then used to build a directed network. This approach is useful because it adds direction and because it is based on inference. In addition to providing a measure of centrality that could be used as a predictor, the empirical analysis compared to other work on Granger causality and directed networks is conducted on a larger sample, both in terms of cryptocurrencies and time period, providing more robust results.

To study the dynamics of the cryptocurrency network, measures of centrality are also calculated on an annual basis to show which coins are gaining or losing centrality in the network. It may be surprising to the reader, but Bitcoin is not the most central coin in the network. There is empirical evidence in this regard showing that the cryptocurrency market is no longer dominated by Bitcoin (e.g., [24]). Among the most central coins in the analysis we have Cardano, Dogecoin, Gridcoin, and Neo, and the coins in the sample exhibit different centrality dynamics, which may be increasing, decreasing, or stable.

The rest of the paper is structured as follows. Section 2 describes the econometric methodology used for the empirical analysis, Section 3 presents the results, and Section 4 concludes the paper.

2. Methodology

2.1. Data

In this study, the following cryptocurrencies are considered: Auroracoin, Bitcoin, Cardano, Dash, Dogecoin, Eos, Ethereum, Firo, Gridcoin, Litecoin, Monero, Namecoin, Nano, Neo, Peercoin, Primecoin, Ripple, Stellar, Tether, Tron, Vertcoin, Zcash. There are several considerations behind this choice. First, these 22 cryptocurrencies are among the oldest and most important, so we can collect data on a long time period. Second, these cryptocurrencies are also used in other empirical work (e.g., [9] or [23]). Third, I selected only those cryptocurrencies for which I could access data for the same time period to build a balanced model. Finally, limiting the number of cryptocurrencies in the sample makes it easier to visualize the results in network form.

I downloaded the closing price series from *yahoo finance* from 2018–01–01 to 2024–01–01. For some cryptocurrencies it was not possible to download earlier dates. All the elaborations were performed with the programming language *R* and the econometric software *Gretl*.

The definition of returns adopted in this work is

$$r_t = \log_e p_t - \log_e p_{t-1} \tag{1}$$

where p_t is the cryptocurrency price at the end of day t, and p_{t-1} is the price at the end of day $t-1$. There are several reasons for using changes in log price rather than simple price changes [18,19,6]. Indeed, log-returns are the yield from holding the security for that day, and they can neutralize most of the price level effect. Moreover, for changes less than $\pm$ 15 per cent, the change in log-price can be approximated to the percentage price change, and it is convenient to look at the data in terms of percentage price changes.

2.2. Correlation analysis

Correlation analysis is useful for obtaining a descriptive overview of the relationships among cryptocurrencies. However, the usual Pearson's correlation coefficient fails to detect reliable correlation for many types of time series [17]. For this reason, as a robustness check, in addition to the Pearson correlation coefficient, I also use the Spearman correlation coefficient, which is less affected by outliers, and the detrended cross correlation analysis (DCCA), which is more effective in addressing other problems, such as spurious correlations [17].

Given two time series, x_t and y_t, with T being the sample size, the *sample Pearson correlation coefficient* (r_{xy}) is computed as

$$r_{xy} = \frac{\sum_{t=1}^{T}(x_t - \overline{x})(y_t - \overline{y})}{\sqrt{\sum_{t=1}^{T}(x_t - \overline{x})^2}\sqrt{\sum_{t=1}^{T}(y_t - \overline{y})^2}} \quad . \tag{2}$$

If x_t and y_t are converted in the respective rank variables $R(x)$ and $R(y)$, the *Spearman correlation coefficient* (r_s) is computed as

$$r_s = \frac{\sum_{t=1}^{T}[R(x_t) - \overline{R(x)}][R(y_t) - \overline{R(y)}]}{\sqrt{\sum_{t=1}^{T}[R(x_t) - \overline{R(x)}]^2}\sqrt{\sum_{t=1}^{T}[R(y_t) - \overline{R(y)}]^2}} \tag{3}$$

which if all T ranks are distinct integers, can be simplified in

$$r_s = 1 - \frac{6\sum_{t=1}^{T} d_t^2}{T(T^2 - 1)} \tag{4}$$

where d is the difference between the two ranks of each observation.

To define the *DCCA* I use the Prass and Pumi framework [21]. Let $\{X_{1,t}\}_{t\in\mathbb{Z}}$ and $\{X_{2,t}\}_{t\in\mathbb{Z}}$ be two stochastic processes and let $\{X_{1,t}\}_{t=1}^{n}$ and $\{X_{2,t}\}_{t=1}^{n}$ be two samples of size n from these processes. The integrated signals $\{R_{k,t}\}_{t=1}^{n}$ are defined as

$$R_{k,t} := \sum_{j=1}^{t} X_{k,j}, k \in \{1, 2\}, t \in \{1, \ldots, n\} \tag{5}$$

while J_l is the $l \times l$ matrix whose $(r, s)th$ element is given by

$$[J_l]_{r,s} = \begin{cases} 1, & if \quad 1 \le s \le r \le l, \\ 0, & if \quad 1 \le r \le s \le l. \end{cases} \tag{6}$$

For $0 < m < n$

$$R_{k,n}^{\langle 1\rangle} = J_n X_{k,n}^{\langle 1\rangle},\ R_{k,m+i}^{\langle i\rangle} = J_{m+i}^{\langle i\rangle} X_{k,m+i}^{\langle 1\rangle},\ i \in \{1, \ldots, n-m\} \tag{7}$$

where $\left\{R_{k,m+i}^{\langle i\rangle}\right\}_{i=1}^{n-m}$ is a sequence of $n - m$ overlapping boxes starting at i and ending at $m + i$ each containing $m + 1$ values from the integrated signal. To better understand the idea of integrated signals and "boxes," the interested reader can look at the examples given in the first two figures of Prass and Pumi's work cited above. For each $k \in \{1, 2\}$ and $i \in \{1, \ldots, n - m\}$, $\widetilde{R}_{k,i}$ is the vector with ordinates $\widetilde{R}_{k,t}(i), i \le t \le m + i$, of a polynomial least-squares fit associated to the *ith* box $R_{k,m+i}^{\langle i\rangle}$, while $E_{k,i}$ is the vector of the error terms of the fit $E_{k,t}, i \le t \le m + i$, in other words

$$\widetilde{R}_{k,t} = P_{m+1} R_{k,m+i}^{\langle i\rangle} = (\widetilde{R}_{k,i}(i), \ldots, \widetilde{R}_{k,m+i}(i))^T, \tag{8}$$

$$E_{k,i} = R_{k,m+i}^{\langle i\rangle} - \widetilde{R}_{k,i} \quad = Q_{m+1} R_{k,m+i}^{\langle i\rangle} = (E_{k,i}(i), \ldots, E_{k,m+i}(i))^T \tag{9}$$

where

$$P_{m+1} := D_{m+1}\left(D_{m+1}^T D_{m+1}\right)^{-1} D_{m+1}^T, \tag{10}$$

$$Q_{m+1} := I_{m+1} - P_{m+1}, \tag{11}$$

$$D_{m+1}^T = \begin{pmatrix} 1 & 1 & \ldots & 1 \\ 1 & 2 & \ldots & m+1 \\ \vdots & \vdots & \ddots & \vdots \\ 1^{\nu+1} & 2^{\nu+1} & \ldots & (m+1)^{\nu+1} \end{pmatrix} \tag{12}$$

with $\nu \in \mathbb{N}$. Finally, we have that

$$f_{k,DFA}^2(m, i) := \frac{1}{m}\sum_{t=1}^{m+i}\left(R_{k,t} - \widetilde{R}_{k,t} \quad (i)\right)^2 = \frac{1}{m} E_{k,i}^T E_{k,i}, \quad k \quad \in \quad \{1, \quad 2\}, \tag{13}$$

$$f_{DCCA}(m, i) := \frac{1}{m}\sum_{t=1}^{m+i}\left(R_{1,t} - \widetilde{R}_{1,t} \quad (i)\right)\left(R_{2,t} - \widetilde{R}_{2,t} \quad (i)\right) = \frac{1}{m} E_{1,i}^T E_{2,i}, \tag{14}$$

$$F_{k,DFA}^2(m) := \frac{1}{n-m}\sum_{t=1}^{n-m} f_{k,DFA}^2(m, i), \tag{15}$$

$$F_{DCCA}(m) := \frac{1}{n-m}\sum_{t=1}^{n-m} f_{DCCA}(m, i), \tag{16}$$

$$DCCA(m) := \frac{F_{DCCA}(m)}{\sqrt{F^2_{1,DFA}(m)}\sqrt{F^2_{2,DFA}(m)}}, \tag{17}$$

where (13) is the sample variance of the residuals $\{E_{k,t}(i)\}_{t=i}^{m+i}$, (14) is the sample covariance between the residuals $\{E_{1,t}(i)\}_{t=i}^{m+i}$ and $\{E_{2,t}(i)\}_{t=i}^{m+i}$, corresponding to the *ith* box, (15) is the detrended variance, (16) is the detrended covariance, and (17) is the detrended cross-correlation coefficient. The interested reader is deferred to other work for further details [20,21].

2.3. VAR model and Granger causality

A VAR(p) model regresses a dependent variable over its lags and the lags of other variables up to the *pth* lag. The selection of the correct p is crucial to properly incorporate autocorrelation into the model, which is why programming languages and statistical software have developed automatic routines that test each model up to a certain number of lags and then choose the best one based on information criteria. Using our sample of 22 cryptocurrencies over 6 years, Bayesian Information Criterion (BIC) and Hannan-Quinn Information Criterion (HQC) selected VAR(1) as the best model, while Akaike Information Criterion (AIC) selected VAR(3) as the best model. I chose VAR(1) for reasons of parsimony, because smaller models are easier to estimate and interpret, and because two of the three available information criteria selected VAR(1) as the best model.

The VAR(1) model to estimate is then made by 22 equations and can be formulated as follows

$$\begin{aligned} C_{1,t} &= \beta_{1,0} + \beta_{1,1}\, C_{1,t-1} + \beta_{1,2}\, C_{2,t-1} + \dots + \beta_{1,22}\, C_{22,t-1} + u_{1,t} \\ C_{2,t} &= \beta_{2,0} + \beta_{2,1}\, C_{1,t-1} + \beta_{2,2}\, C_{2,t-1} + \dots + \beta_{2,22}\, C_{22,t-1} + u_{2,t} \\ &\dots \\ C_{22,t} &= \beta_{22,0} + \beta_{22,1}\, C_{1,t-1} + \beta_{22,2}\, C_{2,t-1} + \dots + \beta_{22,22}\, C_{22,t-1} + u_{22,t} \end{aligned} \tag{18}$$

where $C_{i,t}$ indicates the *ith* cryptocurrency at time t, with, $i = 1, 2, \dots, 22$, the betas are the unknown parameters to be estimated, and u indicates the error the term.

Inference on each $\beta_{i,j}$, with $j = 1, 2, \dots, 22$ being the parameter number, is used to conduct Granger causality tests. In a VAR model, we say that a right-hand side variable Granger causes the left-hand side variable if the beta coefficient is statistically different from zero for some level of significance α. So, for example, if $\beta_{1,2}$ is statistically different from zero at $\alpha = 5\ \%$, this means that C_2 Granger causes C_1 with 95 % of confidence, and we write $C_2 \to C_1$, or equivalently, $C_1 \leftarrow C_2$. If C_1 Granger causes C_2 and C_2 Granger causes C_1, we say that there is bidirectional Granger causality with 95 % confidence, and we write $C_1 \longleftrightarrow C_2$. All these ties are stored in a 22×22 matrix where each c_{hk} entry can be either a 0 or a 1, depending on whether cryptocurrency in row h Granger causes cryptocurrency in column k (in which case we have a 1). This matrix forms the *adjacency matrix* of a directed network with zeros on its diagonal.

It is important to note that although Granger causality contains the word "causality," much empirical work has misused this econometric tool. Indeed, Granger causality does not allow causal relationships to be isolated and should be understood as a tool for finding useful predictors for a variable. In other words, if C_1 Granger causes C_2, then C_1 is a useful predictor for C_2, but we cannot conclude that C_1 causes C_2.

2.4. Network analysis

In this work, three different measures of centrality in a network are considered. The first is *degree centrality*, which can be divided into indegree, outdegree, and total. *Indegree centrality* is a count of the number of links directed to the node, and *outdegree centrality* is the number of links that the node directs to others. *Total degree centrality* is defined as the number of ties incident on a node and is the sum of the other two centrality measures.

The second one is *betweenness*, $B(v)$ with v a vertex, which is a measure of the number of times a node is a bridge along the shortest path between two other nodes. Mathematically, we have that

$$B(v) \quad = \sum_{i,j:\quad i\neq j,\quad i\neq v, v\neq j} \frac{g_{ivj}}{g_{ij}} \tag{19}$$

where g_{ivj} is the number of geodesics from node i to node j that pass-through v, and g_{ij} is the number of geodesics from i to j. Vertices with high betweenness are on a large number of non-redundant shortest paths between other vertices, so higher values of $B(v)$ mean that v act as a bridge for many nodes and is central.

Finally, *eigenvector centrality* or *eigencentrality* measures how influential is a node in a network, in the sense that vertices with high eigenvector centralities are connected to many other vertices which are, in turn, connected to many others (and so on). Mathematically, let G:= (V, E) be a graph with |V| number of vertices and |E| number of edges, and $\mathbf{A} = (a_{vk})$ be the adjacency matrix of the network, with $a_{vk} = 1$ if vertex v is linked to vertex k, $a_{vk} = 0$ otherwise. The relative centrality score of vertex v, x_v, is

$$x_v = \frac{1}{\lambda}\sum_{k\in M(v)} x_k = \frac{1}{\lambda}\sum_{k\in G} a_{vt} x_k \tag{20}$$

where λ is a constant and $M(v)$ is a set of the neighbors of v. We can rewrite (20) as the eigenvector equation

$$\mathbf{Ax} = \lambda\mathbf{x}. \tag{21}$$

There are different eigenvalues λ with a non-zero eigenvector solution and given that the adjacency matrix has non-negative entries, there is a unique largest real and positive eigenvalue, by the Perron–Frobenius theorem, which is the desired centrality measure [14]. The *vth* component of the related eigenvector gives the relative centrality score of the vertex in the network.

3. Results

Before running the model, I checked whether the log-returns series are stationary to avoid spurious correlation problems [17]. Table 1 shows the results of the Augmented Dickey-Fuller (ADF) test using three variants of the test (one without drift and trend, one with drift only, and one with drift and trend). In all cases, we can conclude with high confidence that our series of log-returns are stationary. Table 2 presents some descriptive statistics of the cryptocurrencies log-returns for the entire period. The highest returns over the period were achieved by Auroracoin, Dogecoin, Firo, and Primecoin, while the lowest returns were achieved by Auroracoin, Gridcoin, and Primecoin. By far the most volatile coin is Auroracoin, followed by Primecoin.

I also computed the correlation matrix for the cryptocurrencies in the sample and then used hierarchical clustering to aggregate cryptocurrencies based on complete agglomeration method and the default dissimilarity provided by the *R* function *heatmap()*. Fig. 1 shows a heatmap using Pearson correlation coefficients that highlights which cryptocurrencies are most likely to have some kind of relationship. The lower right corner of the matrix shows that Bitcoin, Ethereum, Litecoin, and Neo exhibit strong correlation with each other and with other coins, while Tether, Auroracoin, and Primecoin are weakly correlated with other coins. Some interesting clusters also emerge, such as that between Bitcoin, Ethereum, and Litecoin, or that between Firo and Nano. These clusters make sense in that, for example, Bitcoin and Litecoin were among the first coins introduced (Bitcoin was actually the first), while Firo and Nano were introduced around the same time.

Figs. 2 and 3 repeat the same process but with Spearman's correlation coefficient and *DCCA*. The patterns that emerge from the analysis in Fig. 1 are generally preserved, regardless of the correlation coefficient adopted, showing that these results are robust.

I then proceed to estimate the VAR(1) model with robust standard errors for heteroscedasticity and autocorrelation. The VAR model is stable, as shown by the inverse root of the VAR with respect to the unit circle (Fig. 4), since all points lie within the circle. Using the Granger causality test, I construct two directed networks: one at the 5 % significance level (Fig. 5) and one at the 10 % significance level (Fig. 6).

With 90 % confidence, not only a lot of unidirectional ties emerged, but also some bidirectional ties. We can see that Monero $\longleftrightarrow$ Dogecoin, Dogecoin $\longleftrightarrow$ Neo, Dogecoin $\longleftrightarrow$ Cardano, Cardano $\longleftrightarrow$ Gridcoin, and Dogecoin $\longleftrightarrow$ Neo, Eos $\longleftrightarrow$ Neo, while at 95 % of confidence the only bidirectional tie surviving is the one between Dogecoin and Cardano, while we have that Vertcoin is an isolated node. However, graphical analysis makes it difficult to appreciate which cryptocurrency is more central in the network, so I calculated the centrality measures introduced in Section 2.4. Tables 3 and 4 show the centrality measures for the networks in Figs. 5 and 6,

Table 1
ADF test p-values on log-returns. The procedure optimally selects the proper number of lags to include testing down from 30 lags using the BIC.

	p-value (no drift)	p-value (drift)	p-value (drift and trend)
Auroracoin	0.0000	0.0000	0.0000
Bitcoin	0.0001	0.0001	0.0000
Cardano	0.0001	0.0001	0.0000
Dash	0.0001	0.0001	0.0000
Dogecoin	0.0000	0.0000	0.0000
Eos	0.0001	0.0001	0.0000
Ethereum	0.0000	0.0000	0.0000
Firo	0.0001	0.0001	0.0000
Gridcoin	0.003	0.0020	0.0020
Litecoin	0.0001	0.0001	0.0000
Monero	0.0050	0.0050	0.0050
Namecoin	0.0000	0.0000	0.0000
Nano	0.0001	0.0001	0.0000
Neo	0.0001	0.0001	0.0000
Peercoin	0.0001	0.0001	0.0000
Primecoin	0.0020	0.0020	0.0000
Ripple	0.0001	0.0001	0.0000
Stellar	0.0001	0.0001	0.0000
Tether	0.0000	0.0000	0.0000
Tron	0.0001	0.0001	0.0000
Vertcoin	0.0001	0.0001	0.0000
Zcash	0.0000	0.0000	0.0000

Table 2
Summary statistics of cryptocurrencies log-returns over the period 2018–2023.

	Min	Mean	Median	Max	SD
Auroracoin	- 1,0133	- 0,0017	0,0000	1,4431	0,1696
Bitcoin	- 0,4647	0,0005	0,0008	0,1718	0,0368
Cardano	- 0,5036	- 0,0001	- 0,0003	0,3218	0,0556
Dash	- 0,4655	- 0,0016	0,0005	0,4513	0,0550
Dogecoin	- 0,5151	0,0011	- 0,0008	1,5163	0,0714
Eos	- 0,5042	- 0,0010	0,0000	0,4396	0,0592
Ethereum	- 0,5507	0,0005	0,0006	0,2307	0,0475
Firo	- 0,5837	- 0,0018	- 0,0009	1,0298	0,0669
Gridcoin	- 1,4087	- 0,0012	- 0,0010	1,1988	0,1087
Litecoin	- 0,4491	- 0,0005	0,0001	0,2906	0,0504
Monero	- 0,5342	- 0,0003	0,0019	0,3450	0,0496
Namecoin	- 1,1598	- 0,0008	0,0001	0,7503	0,0861
Nano	- 0,5858	- 0,0015	- 0,0017	0,7461	0,0698
Neo	- 0,4656	- 0,0008	0,0007	0,3343	0,0579
Peercoin	- 0,6647	- 0,0012	- 0,0019	0,5674	0,0680
Primecoin	- 1,3012	- 0,0015	- 0,0024	1,4945	0,1608
Ripple	- 0,5505	- 0,0006	- 0,0010	0,5486	0,0568
Stellar	- 0,4100	- 0,0006	- 0,0006	0,5592	0,0550
Tether	- 0,0526	- 0,0000	- 0,0000	0,0534	0,0036
Tron	- 0,5231	0,0003	0,0013	0,7867	0,0577
Vertcoin	- 0,6383	- 0,0023	- 0,0034	0,7239	0,0738
Zcash	- 0,5394	- 0,0014	- 0,0004	0,2607	0,0561

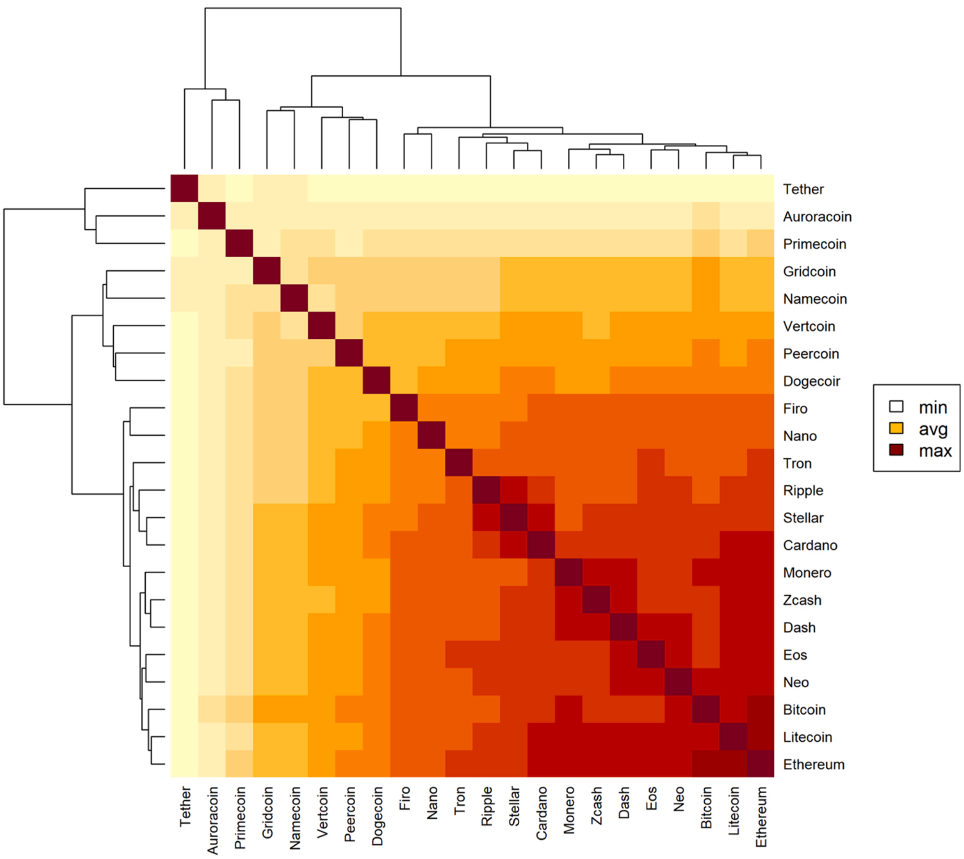

Fig. 1. Heatmap matrix with dendrogram constructed using Pearson correlation coefficient between cryptocurrencies log-returns. Max = 1, avg = 0.43, min = −0.08.

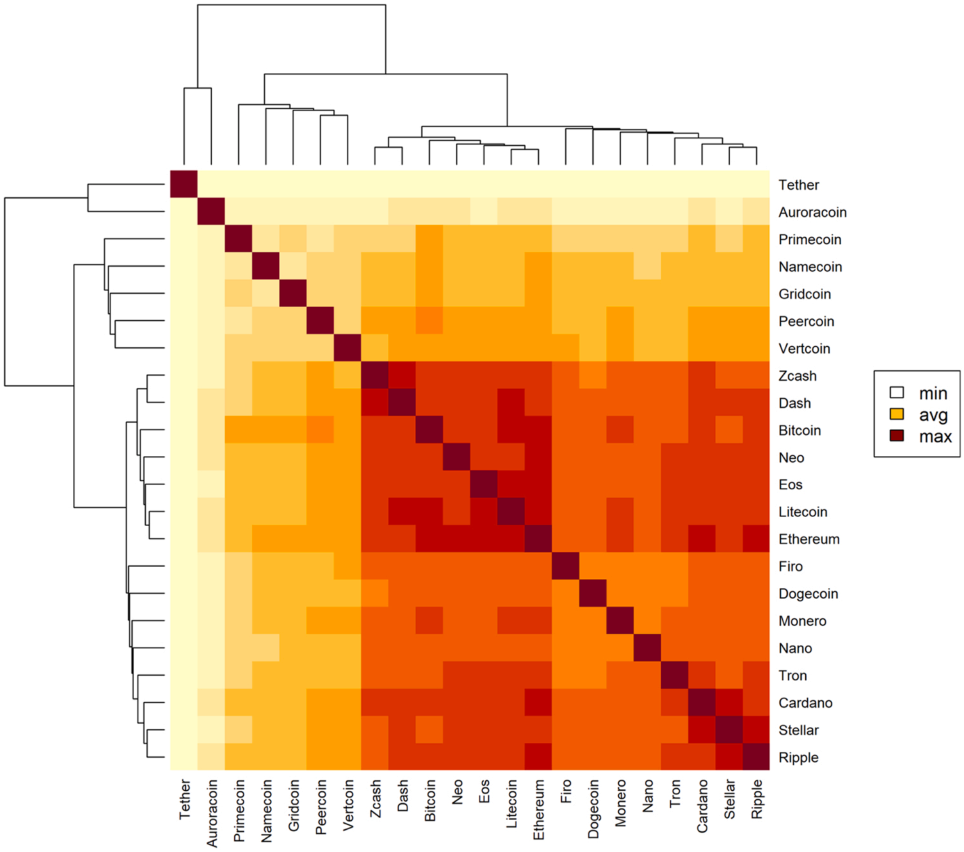

Fig. 2. Heatmap matrix with dendrogram constructed using Spearman correlation coefficient between cryptocurrencies log-returns. Max = 1, avg = 0.49, min = 0.004.

respectively. We focus our attention on Table 3, but similar comments apply to Table 4. The three centrality measures select Cardano, Dash, Dogecoin, Gridcoin, Neo, and Tether as the most central cryptocurrencies in the network. In particular, according to the measures of centrality, Dogecoin seems to be the most central, since it Granger causes the most cryptocurrencies. Neo has almost the same degree centrality as Dogecoin, but lower betweenness and eigenvector centrality because it acts less as a bridge. Surprisingly, Bitcoin is not central in the cryptocurrency network, which shows that the market is no longer dependent on the historically leading currency and has deeply evolved since its inception.

Networks constructed in this way provide a long-term picture of the relationships among cryptocurrencies, but the position of coins in the network is dynamic and changes over time. To capture this dynamic behavior, we can again use the Granger causality approach by applying it to subsamples of the entire period. For example, we can apply the VAR(1) model to 2018 log-returns to construct a first network, then to 2019 log-returns to construct a second network, and so on until 2023. We can then calculate centrality measures each year to see how the position of each coin in the network changes. Doing this at 90 % significance for betweenness centrality and eigenvector centrality yields Figs. 7 and 8.

The analysis of betweenness over the years highlights many interesting aspects. We can see that the highest values of betweenness have been achieved by Dogecoin, Monero, Neo, and Primecoin, while the highest values of eigencentrality have been achieved by Cardano, Dogecoin, and Gridcoin, and these numbers partially confirm the analysis on the full sample. While the centrality of Dogecoin and Neo has decreased over the years, Gridcoin has gained centrality in recent years, as both measures of centrality show an increasing trend. This conclusion results from estimating the trend of the series using OLS. Focusing on eigencentrality for the sake of synthesis (and because as we shall see it is the most relevant measure), we have that the estimated slope of the linear trend for Dogecoin eigencentrality is -0.12, the estimated slope for Neo eigencentrality is -0.08, while for Gridcoin is 0,06. Thus, the results in Table 4 are likely driven by the early years of our sample for Dogecoin and Neo, while the later years weigh more heavily for Gridcoin and its position in the network. There are coins that are gaining centrality over the years, such as Litecoin (estimated slope of eigencentrality trend = 0.04), Namecoin (estimated slope of eigencentrality trend = 0.06), or Ripple (estimated slope of eigencentrality trend = 0.05). Moreover, this dynamic analysis confirms that Bitcoin is no longer to be considered the “center” in the crypto network. In fact, Bitcoin’s centrality scores are always moderate with no particular trend (estimated slope of eigencentrality trend = 0.01). As in other empirical work, the dynamic analysis confirms that Ethereum has gained centrality over the years (estimated slope of eigencentrality trend = 0.03), while, despite having some connections in the network, having estimated a negative slope of -0.03 for the eigencentrality trend,

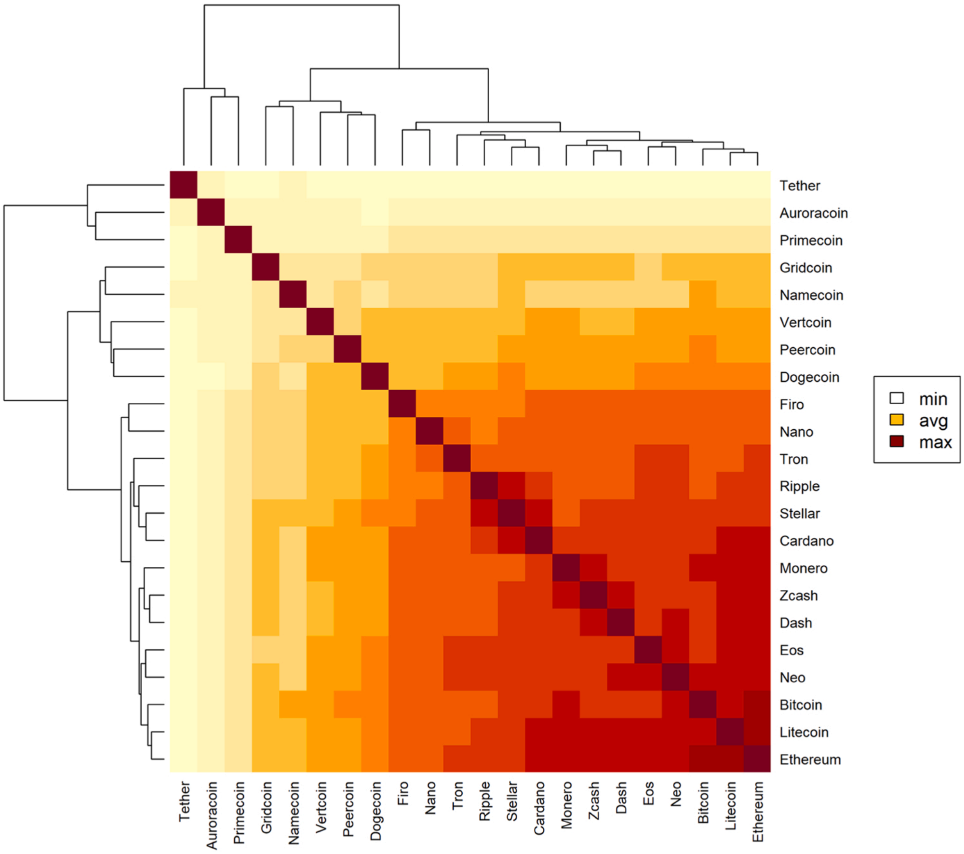

Fig. 3. Heatmap matrix with dendrogram constructed using *DCCA* between cryptocurrencies log-returns. Max = 1, avg = 0.42, min = −0.07.

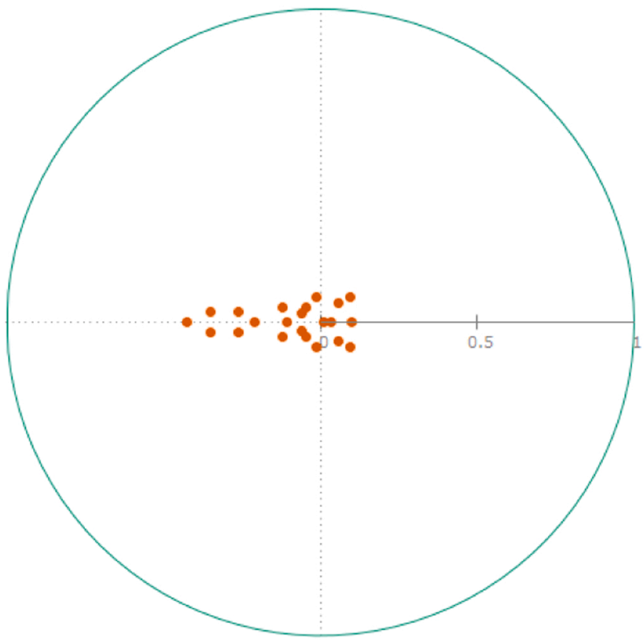

Fig. 4. VAR roots in relation to the unit circle.

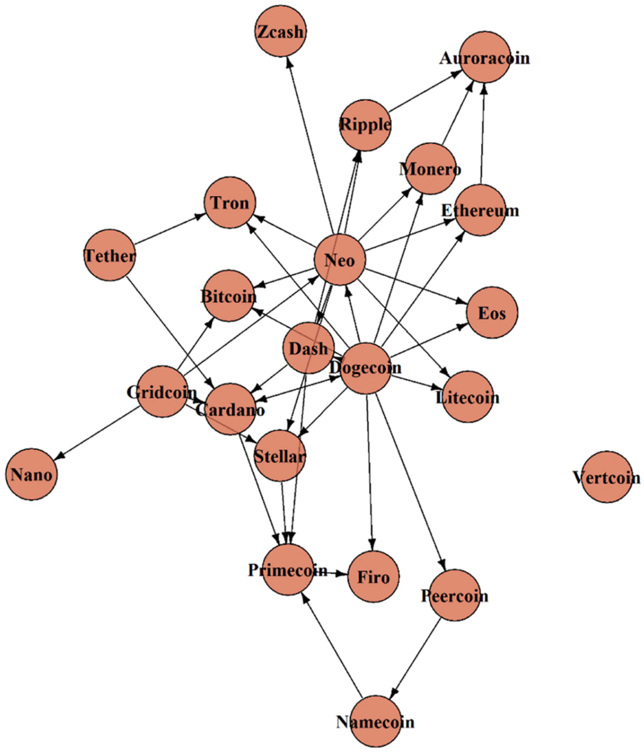

Fig. 5. Directed network built using the Granger causality test at 5 % of significance.

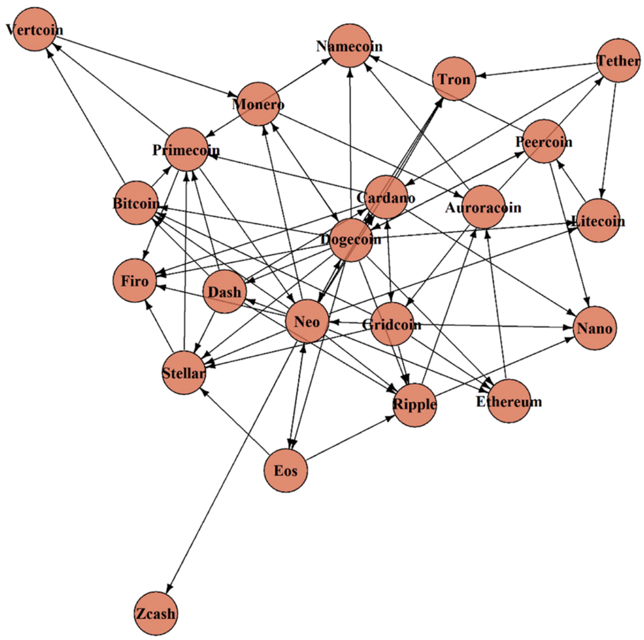

Fig. 6. Directed network built using the Granger causality test at 10 % of significance.

we cannot conclude that Eos exhibit increasing centrality (differently from [24]).

The centrality measures derived in this paper can be used as predictors in a regression framework. To see how centrality in cryptocurrency networks is related to returns, I developed two (crypto-assets) fixed-effects models with time dummies for annual log-returns, using betweenness or eigencentrality as independent variables. These are panel data models consisting of 22 crypto-assets and

Table 3
Centrality measures for the network of Fig. 5.

	Total degree	Indegree	Outdegree	Betweenness	Eigenvector
Auroracoin	3	3	0	0.0000	0.0000
Bitcoin	3	3	0	0.0000	0.0000
Cardano	6	4	2	35.000	0.4345
Dash	5	2	3	6.8333	0.2965
Dogecoin	13	1	12	43.333	0.6368
Eos	2	2	0	0.0000	0.0000
Ethereum	3	2	1	2.1666	0.0000
Firo	2	2	0	0.0000	0.0000
Gridcoin	5	0	5	0.0000	0.4345
Litecoin	2	2	0	0.0000	0.0000
Monero	3	2	1	2.1666	0.0000
Namecoin	2	1	1	2.0000	0.0000
Nano	1	1	0	0.0000	0.0000
Neo	12	2	10	14.500	0.2023
Peercoin	2	1	1	6.0000	0.0000
Primecoin	5	4	1	6.6666	0.0000
Ripple	3	2	1	1.6666	0.0000
Stellar	4	3	1	2.1666	0.0000
Tether	2	0	2	0.0000	0.2965
Tron	3	3	0	0.0000	0.0000
Vertcoin	0	0	0	0.0000	0.0000
Zcash	1	1	0	0.0000	0.0000

Table 4
Centrality measures for the network of Fig. 6.

	Total degree	Indegree	Outdegree	Betweenness	Eigenvector
Auroracoin	6	3	3	58.452	0.1382
Bitcoin	6	4	2	9.0095	0.0728
Cardano	11	5	6	41.019	0.3114
Dash	7	2	5	0.7833	0.1966
Dogecoin	18	4	14	87.169	0.5633
Eos	5	2	3	0.0000	0.1788
Ethereum	4	3	1	6.5095	0.0409
Firo	5	5	0	0.0000	0.0000
Gridcoin	9	2	7	41.166	0.3046
Litecoin	4	3	1	7.5000	0.0540
Monero	5	3	2	29.600	0.2075
Namecoin	5	4	1	8.9666	0.0547
Nano	4	4	0	0.0000	0.0000
Neo	17	4	13	100.82	0.5091
Peercoin	5	2	3	21.166	0.1828
Primecoin	9	5	4	67.861	0.1849
Ripple	7	5	2	16.176	0.0409
Stellar	7	5	2	4.8595	0.0547
Tether	4	1	3	12.100	0.1081
Tron	4	4	0	0.0000	0.0000
Vertcoin	3	2	1	7.8333	0.0613
Zcash	1	1	0	0.0000	0.0000

6 time periods, for a total of $22 \times 6 = 132$ observations. The dependent variable is represented by r_{it} in both models, which is the log-return of cryptocurrency *i* at time *t*. The explanatory variable in the first model is betweenness centrality, while in the second model it is eigencentrality. The models are described by the following equations (estimated independently):

$$r_{it} = \alpha + \beta \ betweenness + \gamma_i + \delta_1 \ D2019 + \delta_2 \ D2020 + \delta_3 \ D2021 + \delta_4 \ D2022 + \delta_5 \ D2023 + e_{it} \tag{22}$$

$$r_{it} = \alpha + \phi \ eigencentrality + \gamma_i + \delta_1 \ D2019 + \delta_2 \ D2020 + \delta_3 \ D2021 + \delta_4 \ D2022 + \delta_5 \ D2023 + u_{it} \tag{23}$$

where γ_i are crypto-assets fixed-effects (the same greek letter in the two equations for simplicity) to account for unobserved heterogeneity, the δs (the same greek letters in the two equations for simplicity) are the coefficients of the time dummies (e.g., D2019 is a dummy variable equal to 1 for observations in 2019 and 0 otherwise), β and ϕ are the coefficients that measures the relationship between centrality measures and log-returns, and *e* and *u* are the error terms.

The results of these models are shown in Table 5. We can see that while betweenness centrality appears to have no relationship with log-returns, eigencentrality is highly significant and has a positive coefficient. This means that each one unit increase in eigencentrality is associated with a 0.22 percent increase in log-returns, suggesting that more central cryptocurrencies are more profitable. In addition,

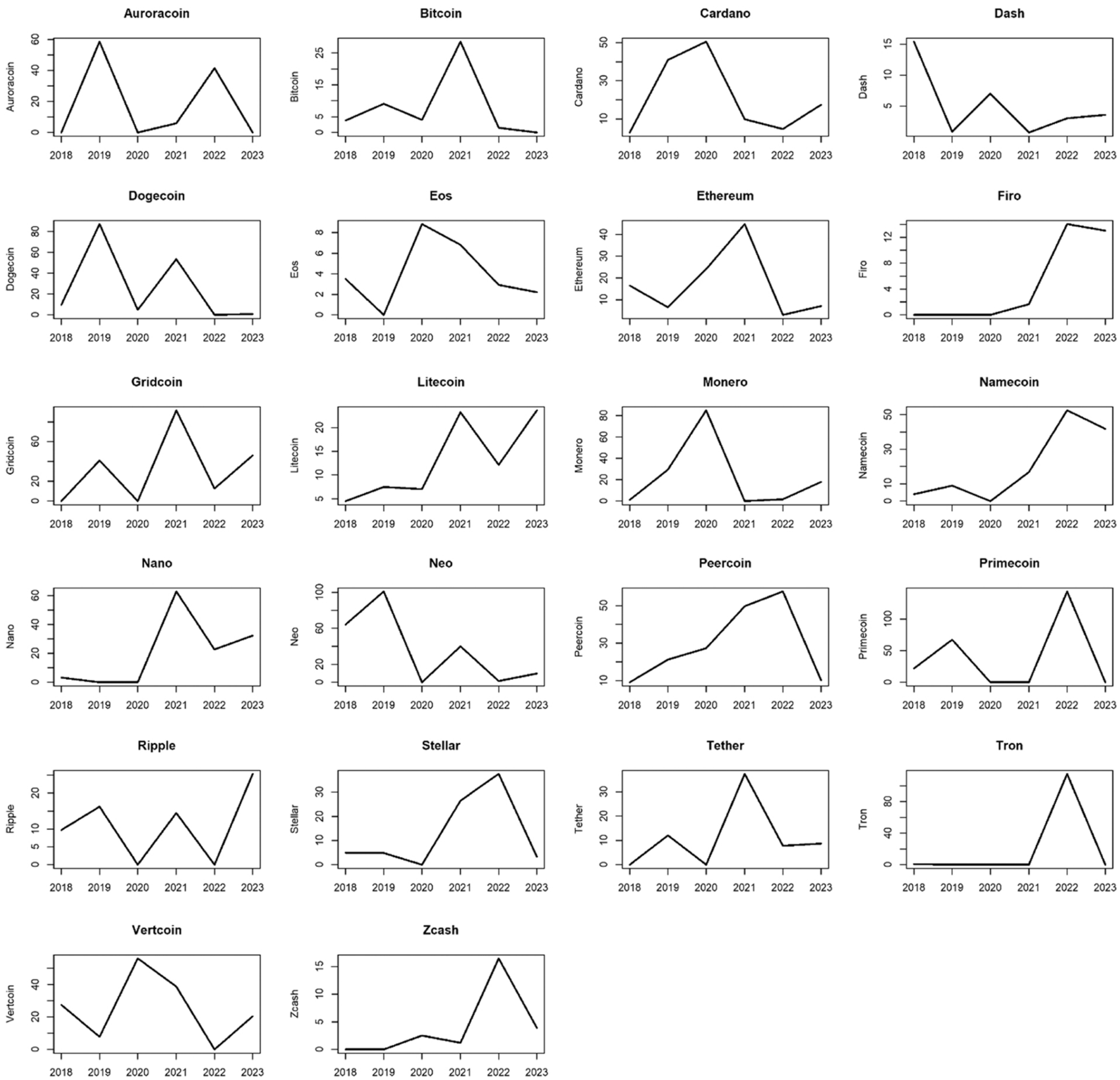

Fig. 7. Betweenness centrality of cryptocurrencies over the period 2018–2023.

the model with eigencentrality as a regressor is clearly better than the model with betweenness, since all selection criteria (coefficient of determination and information criteria) point to the former as the better model (higher coefficient of determination and lower information criteria).

4. Conclusions

This work has provided further evidence in favour of the idea that the crypto-market is highly interconnected. Using an approach based on Granger causality, I derive directed network and computed centrality measures. There are several important conclusions from this empirical analysis. First, the paper confirms again that many cryptocurrencies are highly correlated; moreover, there are many unidirectional links between cryptocurrencies, while very few bidirectional links. This means that shocks will not affect cryptocurrencies in the same way, as shocks affecting more central coins risk to propagate faster. This is the case, for example, for Dogecoin, Cardano or Neo, which are central coins in the network. Second, I find evidence that eigencentrality is associated with higher log-returns, so the more influential a coin in the network the higher the remuneration from investing in that coin. Despite the significance of these results, there may be factors that limit their generality, such as small sample size and omission of factors that fixed effects cannot take care of. For this reason, further evidence should be collected using a larger sample and more covariates, and this could be work for future research.

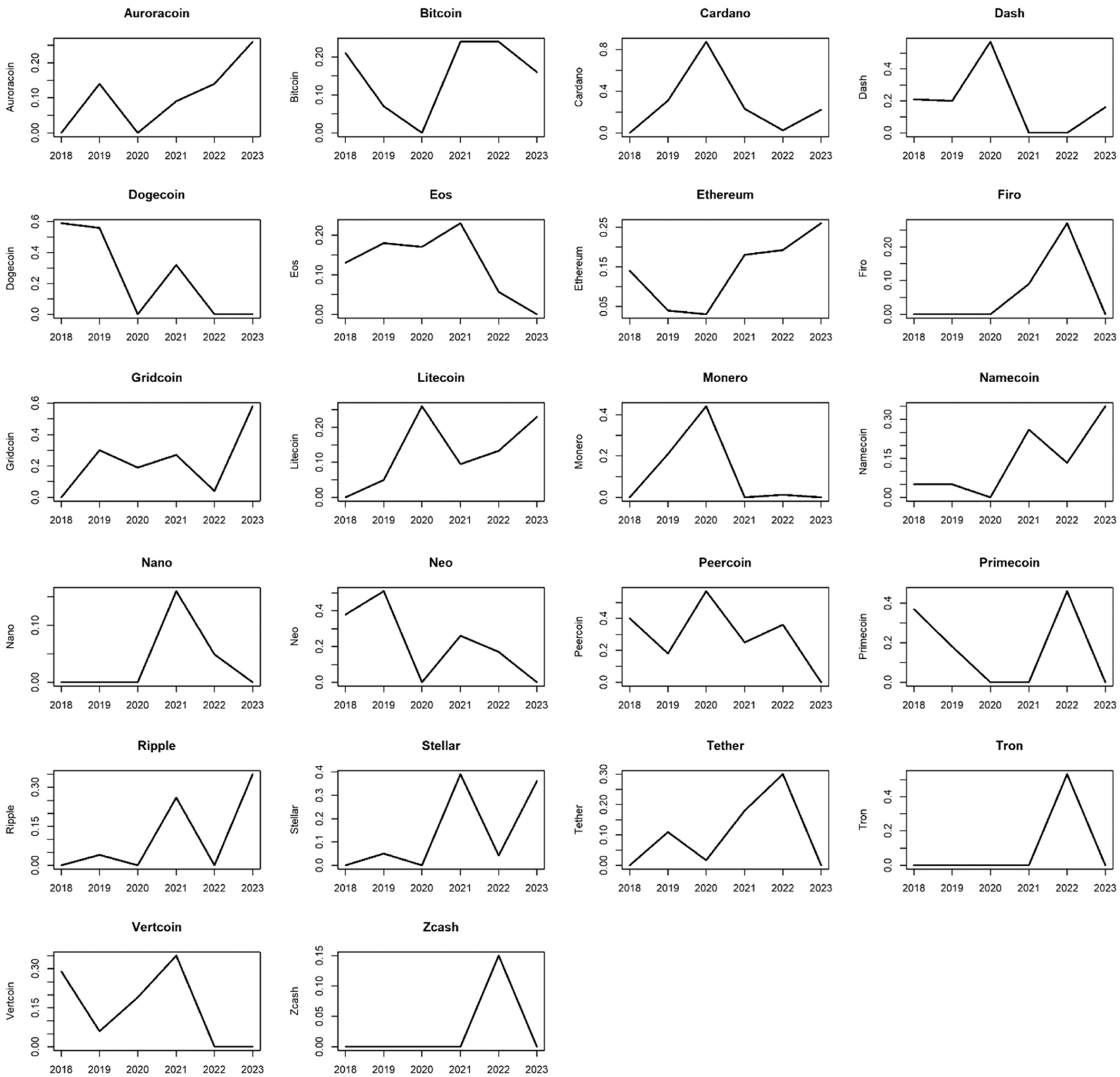

Fig. 8. Eigenvector centrality of cryptocurrencies over the period 2018–2023.

Finally, the framework can be extended to derive measures of centrality over smaller time periods or other useful network metrics. This will provide useful predictors for building better forecasts of cryptocurrency market dynamics.

CRediT authorship contribution statement

Giuseppe Pernagallo: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest

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.

Table 5
Regressions with crypto-assets fixed effects (Arellano robust standard errors) with yearly log-returns as dependent variable. The top panel shows the estimates from Eq. (22), while the bottom panel shows the estimates from Eq. (23).

	Coefficient	SE	t	p-value
Constant	−0.0058	0.0004	−13.55	0.0000
Betweenness	0.0000	0.0000	0.8872	0.3850
Obs.	132			
AIC	−1277.653			
BIC	−1196.935			
LSDV R-squared	0.7862			
Within R-squared	0.7715			
Durbin-Watson	2.0574			
Time dummies	Yes			
	Coefficient	SE	t	p-value
Constant	−0.0060	0.0004	−14.08	0.0000
Eigencentrality	0.0022	0.0006	3.965	0.0007
Obs.	132			
AIC	−1283.614			
BIC	−1202.895			
LSDV R-squared	0.7956			
Within R-squared	0.7816			
Durbin-Watson	2.0158			
Time dummies	Yes			

Data availability

Link for data provided in the paper

Acknowledgments

The author would like to thank the two anonymous reviewers for helpful comments that improved this paper, the main editor Prof. Tiziana Di Matteo and the editor of the special issue Prof. Leonardo Henrique Silva Fernandes for their work.

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