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Dynamic evolution of causal relationships among cryptocurrencies: an analysis via Bayesian networks

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Abstract

Understanding the relationships between cryptocurrencies is important for making informed investment decisions in this financial market. Our study utilises Bayesian networks to examine the causal interrelationships among six major cryptocurrencies: Bitcoin, Binance Coin, Ethereum, Litecoin, Ripple, and Tether. Beyond understanding the connectedness, we also investigate whether these relationships evolve over time. This understanding is crucial for developing profitable investment strategies and forecasting methods. Therefore, we introduce an approach to investigate the dynamic nature of these relationships. Our observations reveal that Tether, a stablecoin, behaves distinctly compared to mining-based cryptocurrencies and stands isolated from the others. Furthermore, our findings indicate that Bitcoin and Ethereum significantly influence the price fluctuations of the other coins, except for Tether. This highlights their key roles in the cryptocurrency ecosystem. Additionally, we conduct diagnostic analyses on constructed Bayesian networks, emphasising that cryptocurrencies generally follow the same market direction as extra evidence for interconnectedness. Moreover, our approach reveals the dynamic and evolving nature of these relationships over time, offering insights into the ever-changing dynamics of the cryptocurrency market.

Keywords Cryptocurrencies · Bayesian networks · Sensitivity analysis · Casual analysis · Structure learning

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1 Introduction

Due to factors such as enhanced transaction privacy and as a alternative to centralised financial systems, the cryptocurrency market has gained wider acceptance and shown marked growth [16]. This is evident in the diversity of available coins and the increase in overall market capitalisation. For instance, the market capitalisation has increased from 10 billion US dollars in January 2014 to 1.3 trillion US dollars in October 2023. When compared with gold's market capitalisation of $13 trillion, the cryptocurrency market's significance is evident.[1] Furthermore, as a relatively new financial instrument, the cryptocurrency market, due to its unique nature, faces several challenges. These include regulatory uncertainties from government bodies [17] and the risk of cryptocurrencies being involved in illicit activities [21]. Another factor that adds complexity to this market is the inherent volatility of cryptocurrency prices, which poses considerable risk for investors. An example of this volatility can be seen in the dramatic changes in total market capitalisation. To illustrate, between January 2020 and November 2021, the cryptocurrency market's capitalisation surged from 213.9 billion US dollars to 2.9 trillion US dollars. However, it subsequently declined, settling at 1.2 trillion US dollars by May 2023. These dramatic fluctuations highlight the critical importance of understanding the underlying factors driving these price changes. Such understanding is invaluable not just for price prediction but also for effective portfolio management.

Understanding the relationships among financial assets is important, as it provides valuable insights into market integration and quantifies the influence various assets have on one another [20, 29]. Analysing these relationships is a crucial part of both fundamental and technical analysis in the cryptocurrency market, which explains the complexities of the economy and offers practical benefits such as effective investment portfolio strategies and risk management [26]. While substantial research has explored traditional financial assets, the study of relationships among cryptocurrencies is still in its early stages, since they are relatively new[10]. Besides several studies concerning relationships among cryptocurrencies[6, 25, 28], exploring the causal relationship among them is somewhat less investigated to the best of our knowledge after searching several frequent academic publication databases. As the cryptocurrency market is an emerging field, two critical factors require further investigation to deepen our understanding of the connections among different cryptocurrencies. Firstly, it is crucial to determine whether these coins follow traditional financial dynamics. Secondly, as highlighted by Aslanidis et al. [7], there is a need to evaluate the nature of these relationships, whether they are stable or evolve over time. Particularly, understanding the interconnectivity of cryptocurrency prices is a vital task. This not only enables the characterisation of price relationships but also provides invaluable insights into market efficiency. By assessing whether fluctuations in the prices of one cryptocurrency affect others, we can evaluate the degree of interdependence and the potential spillover effects within the cryptocurrency market [15].

The dynamics among cryptocurrencies have attracted considerable scholarly attention, yielding important findings. In a study by Stosic et al. [33], the relationships among 119 cryptocurrencies are examined, which reveals a non-trivial hierarchical grouping based on their cross-correlation matrix. Building on this research, Shi et al. [31] employ a multivariate factor stochastic volatility model to analyse the dynamic correlations among six cryptocurrencies. Their outcomes replicate the earlier findings, revealing smaller groups of cryptocurrencies with similar price volatility levels. In a study exploring market integration, Bouri et al. [10] investigate twelve cryptocurrencies using the dynamic equicorrelation model. They discover that the interconnectedness among cryptocurrencies is not static but

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evolves over time. Smales [32] investigates return and volatility spillovers among Bitcoin, Ethereum, and Tether, employing multivariate GARCH models. The results underscore the presence of time-varying conditional correlations among these cryptocurrencies, which highlight a bidirectional relationship in returns between Bitcoin and Ethereum. Interestingly, Tether demonstrates limited influence on volatility transmission within the cryptocurrency market. Another study by Almeida et al. [4] applies cross-correlation analysis to investigate the impact of the pandemic on the relationships among 16 cryptocurrencies, with a specific focus on market integration and contagion. The research uncovers that the pandemic contributed to increased integration among cryptocurrencies, with an overall increase in correlation levels and market integration during the COVID-19 period compared to the pre-pandemic period. A study by [2] examines volatility spillovers among two cryptocurrencies (Bitcoin and Ethereum), two NFTs (Tezos and The Sandbox), and two DeFi assets (Chainlink and Uniswap) using a time-varying parameter vector autoregression model. The results indicate that Ethereum and Chainlink primarily transmit volatility, impacting other crypto assets, while the others are more likely to receive it. The study also highlights a relatively lower volatility connection among NFT assets and underscores the evolving roles of these assets, particularly under fluctuating market conditions during the COVID-19 pandemic. The study by [25] explores the spillovers and relationships among leading cryptocurrencies like Bitcoin, Ethereum, and Monero using spillover index and wavelet approaches. The research highlights dynamic spillovers influenced by news releases and varying market conditions, such as during the COVID-19 pandemic. Findings indicate that a portfolio combining multiple cryptocurrencies reduces risk better than one consisting only of Bitcoin.

These studies share two key aspects. Firstly, the presence of interconnected groups within the cryptocurrency ecosystem is revealed by specific clusters of cryptocurrencies that exhibit similar patterns of price fluctuations. Secondly, they highlight the dynamic nature of relationships among different cryptocurrencies. These relationships, encompassing correlations and market integration, are not fixed but rather evolve in response to numerous factors and changing market conditions. It is important to mention that the existing body of literature on cryptocurrencies has primarily focused on correlation analysis to assess their relationships. While correlation analysis provides valuable insights into associations, it lacks in discovering causality and the directional influence among cryptocurrencies. Therefore, it is crucial to consider these limitations and adapt to the distinctive characteristics of cryptocurrencies when conducting analyses to understand their complex relationships.

In this study, we attempt to address the limitations inherent in previous cryptocurrency research by adopting Bayesian networks (BNs). Particularly, we aim to extract causal relationships among cryptocurrencies using BNs. These networks are recognised for their proficiency in modelling complex systems, such as financial markets, and offer a robust solution. They are valuable tools in managing uncertainty and nonlinearity and excel at handling a large number of data features, making them particularly suitable for this context. BNs provide effective mechanisms for representing and reasoning about probabilistic relationships among variables [30]. Notably, unlike traditional correlation analysis, BNs offer a structured framework for determining whether one cryptocurrency exerts an influence over the price changes of others. By conducting a thorough causal relationship analysis, we focus on understanding the complex interactions inherent in the cryptocurrency sector, thus enabling us to achieve a comprehensive understanding of their relationships and predictive patterns.

This study employs BNs to uncover the causal dynamics among six leading cryptocurrencies, examining how the price of one can influence the fluctuations of the others. Furthermore, the research presents an approach to exploring the dynamic relationship between cryptocurrencies. In particular, we introduce a procedure for constructing BNs that enables the exploration of the evolving nature of these relationships.

The contributions of this paper are as follows:

- **Uncovering Causal Relationships:** By employing BNs, we uncover the causal relationships among the six major cryptocurrencies, clarifying the directional influence they exert on one another.
- **An approach for investigating the dynamic causal structure of BNs:** We extend beyond static analysis by employing a technique that captures the temporal shifts in the interconnectedness among cryptocurrencies. This approach offers insights into the evolving cryptocurrency market, facilitating a deeper understanding of its changing patterns and behaviours.

2 Bayesian networks overview

BNs represent an effective modelling framework for designing knowledge structures that have found widespread application in various fields [19]. These models are widely employed for the modelling of stochastic systems, facilitating a range of analytical tasks, including probabilistic prediction and decision-making [9]. Rooted in the foundational principles of conditional probability and Bayesian theory, BNs offer an elegant tool to capture and represent complex systems, particularly those characterised by stochastic behaviour, interdependencies, and causal relationships. These graphical models provide a structured way to encode knowledge, explore probabilistic relationships among variables, and facilitate decision-making processes [24]. With their ability to seamlessly integrate expert insights, conduct probabilistic inference, and make informed predictions, BNs are indispensable tools in a broad spectrum of domains, from healthcare and finance to environmental management and beyond [8].

BNs utilise directed acyclic graphs (DAGs) to represent the complex connections among random variables [3]. In a particular network, nodes within the graph symbolise individual variables, while the direction of edges outlines causal pathways, facilitating causal inferential analysis. Additionally, each node in the network is linked with a probability distribution, typically represented by conditional probability tables (CPTs). These tables explain the probabilities associated with the potential values of a node based on the probabilities of its parent variable(s). Mathematically, for a given system comprising a set of random variables denoted as $X_1, X_2, \ldots, X_n$, the joint probability distribution function within a BN can be briefly expressed as:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|\text{parents}(X_i)). \tag{1}$$

Here, $\text{parents}(X_i)$ represents the group of parent variables influencing X_i within a DAG representation of the BN. Equation (1) forms the core of BN modelling, enabling a comprehensive understanding of complex probabilistic relationships and further inferential analysis.

The construction of a BN can be accomplished through various methods, including the manual input of domain experts' knowledge, the automated generation using computer programs with extensive training data (a data-driven approach), or a hybrid approach that combines both methods [35]. Learning the structure of a BN directly from data represents an expanding field within machine learning. However, it poses substantial challenges, even when complete datasets are readily available [14].

3 Experiment design

To analyse the relationships between six popular cryptocurrencies, we combine price-related time series data for each cryptocurrency, creating a unified dataset with consistent time granularity. Subsequently, we normalise this dataset using the min-max normalisation technique.[2] As most software packages for BN construction need a discretisation preprocessing step, it becomes necessary to discretise continuous price data. This discretisation process involves the selection of an appropriate discretisation method and the determination of the number of bins for continuous data discretisation [27]. In this study, we adopt the optimal discretisation method and bin numbers based on a comprehensive analysis outlined in [5]. Specifically, we employ the k-means clustering algorithm with two bins to define the states of BN nodes. The state 'Down' signals a price decrease, where today's closing price is lower than the previous day's closing price, while 'Up' signals the opposite.

This study introduces an innovative approach to analysing cryptocurrency relationship dynamics. The method involves the utilisation of an expanding window technique, wherein the dataset is partitioned into several sub-datasets. For each sub-dataset, a BN is constructed to capture the interrelationships among the six cryptocurrencies. Specifically, the expanding window starts with a 90-day window size and progressively extends by 30 days, resulting in 59 sub-datasets. For each sub-dataset, we construct a BN and count the edges where a cryptocurrency serves as the parent node of other cryptocurrencies. Then, based on this information, a BN is created, and it is compared with the final BN constructed based on the whole dataset. By comparing the relationships across the nodes within each BN and the final BN, potential changes in these relationships over time can be detected. This approach provides valuable insights into the changing relationships between cryptocurrencies across time and investigates whether the relationships evolve over time.

The process of building BNs from sub-datasets and analysing their edges is implemented in Python, using the GeNIe [8] software package through the PySMILE wrapper for Bayesian inference and BN modification. The experiments are performed on a Windows 10 Enterprise operating system, running an Intel i7-Core(TM) CPU @ 1.90GHz, 2.11 GHz processor, and 16.0 GB of RAM.

3.1 Data

We select Bitcoin, Binance Coin, Ethereum, Litecoin, Ripple, and Tether as the set of cryptocurrencies for several reasons. Bitcoin's market capitalisation accounted for 45% of the total market in April 2023, emphasising its position as a dominant force in the cryptocurrency market. Furthermore, these altcoins (cryptocurrencies other than Bitcoin) consistently ranked within the top ten cryptocurrencies by market capitalisation for an extended period, collectively representing over 30% of the cryptocurrency market's value at the beginning of 2023. As a result, these cryptocurrencies all together constitute a substantial portion of the overall cryptocurrency market. To ensure the significance of our analysis, we set a minimum of 1,800 observations, equivalent to at least five years of daily data, providing a sufficient sample size. Moreover, the choice of the time interval is important, as the characteristics of temporal data can influence results [1]. Trading rules vary with the timeframe preferences of

[2] It should be noted that to address the issues associated with the time series of price data, we conduct the augmented Dickey–Fuller (ADF) test for stationarity. Subsequently, we transform the data into a stationary time series format by differencing resulting in the reduction or elimination of trends. The results of the ADF test are detailed in Appendix A.

Table 1 Summary statistics of cryptocurrency prices

	Mean	Std	Min	Median	Max
Binance Coin	146.93	182.79	1.51	29.40	675.68
Bitcoin	20107.80	16803.06	3236.76	11515.22	67566.83
Ethereum	1129.98	1187.30	84.31	518.85	4812.09
Litecoin	101.32	63.59	23.46	74.47	386.45
Ripple	0.52	0.36	0.14	0.38	1.84
Tether	1.00	0.01	0.97	1.00	1.08

The columns provide descriptive statistics of the six cryptocurrency prices in this study. The total number of observations is 1881

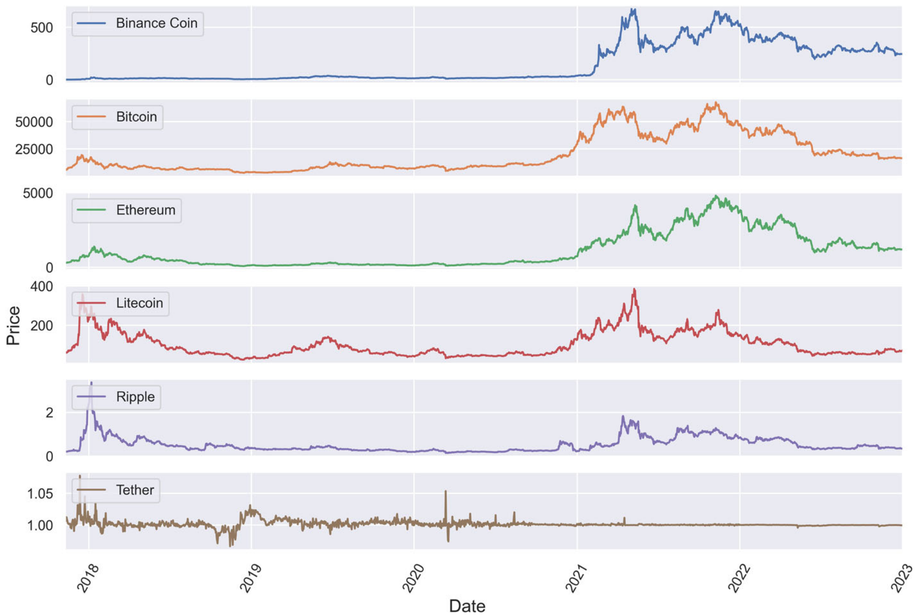


Fig. 1 Price fluctuation of the cryptocurrencies in this study from 2018 to 2023

financial market participants and should be linked to specific time granularities. For instance, while swing traders examine daily and weekly data, day traders focus on high-frequency data such as hourly prices [12]. Our choice of the time interval is essentially aligned with existing studies including [13, 18, 23]. Daily data are primarily selected as they enable the observation of broader market trends between cryptocurrencies without the noise of higher frequency fluctuations. It is noteworthy that the proposed method is designed to offer flexibility across various time granularities, thereby accommodating the diverse needs of traders and investors in creating strategies. The daily price data for these six cryptocurrencies are collected between November 2017 and January 2023 using the yfinance Python package, sourced from Yahoo Finance. For a comprehensive overview of the dataset, refer to Table 1 for descriptive statistics.

In Fig. 1, we present a visual depiction of cryptocurrency prices, offering valuable insights into the dataset. The chart reveals a period of relative stability and upward price trends for

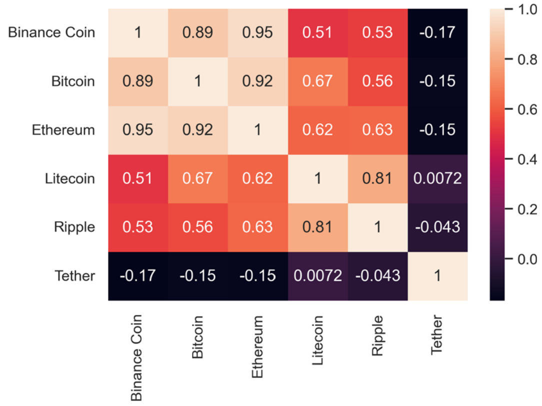


Fig. 2 The correlation matrix of cryptocurrencies visualises the strength of correlation between two cryptocurrencies. The intensity of this correlation is represented by the colour shading, as explained in the legend on the right-hand side (color figure online)

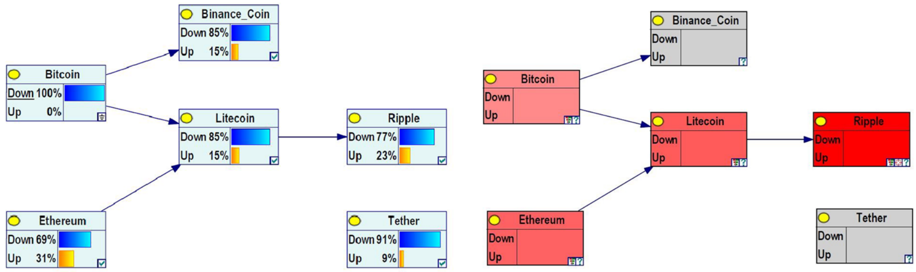
all the coins until 2020. However, fluctuations in price volatility become evident during and after 2021. It is worth highlighting that Tether's price maintains consistent stability, reflecting its characteristics as a stablecoin. A stablecoin is backed by stable assets, which, in the case of Tether, is the US dollar. Both this figure and the insights offered in Table 1 emphasise the significance of understanding and addressing the inherent volatility in the cryptocurrency market.

4 Results

This section presents the findings of our study on relationships between cryptocurrencies using BNs. First, the results of the causal analysis with correlational relationships are compared for further insights. Then, we perform diagnosis and sensitivity analyses on the BNs to develop an understanding of these causal relationships. Eventually, we investigate potential changes in the causal relationships based on the proposed approach.

A correlation matrix serves as a valuable tool for gaining a preliminary understanding of the relationships within variables in a dataset. It accomplishes this by displaying correlation coefficients between pairs of variables. In our study, we specifically use Pearson's correlation coefficient, one of the most commonly used methods for computing correlations [34]. This method helps to understand how the price movement of one cryptocurrency may influence the price movements of other cryptocurrencies. Figure 2 presents the correlation matrix of the selected cryptocurrencies, revealing two key insights. Firstly, mining-based coins exhibit positive correlations, though with varying strengths. For instance, Binance Coin shows strong positive relationships with Ethereum and Bitcoin, featuring correlation coefficients of 0.95 and 0.92, respectively. When excluding Tether from the analysis, the remaining cryptocurrencies also show positive correlations, each with its own distinct value. Moreover, by utilising the correlation matrix depicted in Fig. 2, it becomes apparent that certain groups of cryptocurrencies cluster together based on the magnitude of correlation between their prices. Here, Tether behaves as an outlier, displaying a distinct correlational pattern compared to other cryptocurrencies. It demonstrates negligible negative correlations with other coins, highlighting its unique role in the cryptocurrency market.

This study employs a data-driven approach to construct a BN for examining the relationships between cryptocurrencies. Figure 3 provides a visual representation of the BN, which is created by considering the entire dataset.



(a) A BN represents the influence relationships between cryptocurrencies incorporating the whole dataset. By setting Bitcoin to its 'Down' state, a diagnostic analysis can be conducted.

(b) This BN shows an example of a sensitivity analysis by setting Ripple as the target node. It shows that prices of Binance Coin and Tether do not have an effect on Ripple's prices.

Fig. 3 The BN constructed for six cryptocurrencies based on the whole price data between 2017 and 2023 showing **a** an example of diagnostic analysis and **b** an example of sensitivity analysis

Analysing the BN's structure is a valuable approach for gaining insights into the relationships represented by the network. It enables the identification of closely related cryptocurrencies in terms of influence and those that exhibit more independent behaviour. The presence or absence of edges between nodes in the network signifies the existence or absence of relationships between the corresponding cryptocurrencies. Figure 3 offers a graphical representation of the interconnectedness of the cryptocurrencies in this study, utilising data from the entire timeframe. In this BN, Bitcoin and Ethereum, two of the top cryptocurrencies by market capitalisation, are the root nodes. Bitcoin has two child nodes, Binance Coin and Litecoin, and is the ancestor of Ripple.[3] Ethereum has one child node, Litecoin, and is the ancestor of Ripple. Notably, Tether is entirely isolated from other cryptocurrencies within the BN, highlighting its unique behaviour in the market, attributed to its distinct coin issuance mechanism. This result is aligned with other studies such as [32].

To gain further insights and understand the dynamics of the system, we perform diagnostic inference and sensitivity analysis on the constructed network as represented in Figs. 3a and 3b. These analyses allow us to simulate different scenarios and examine how changes in one variable may influence the rest of the system.

The diagnostic inference analysis facilitates bidirectional inferences involving both prediction (from cause to effect) and diagnosis (from effect to cause) [22]. This analysis enables us to explore the changes in the CPTs of other nodes when a specific node is fixed in one of its states. In a typical BN scenario depicted in Fig. 3a, we set Bitcoin to the 'Down' state and observe the effects on other cryptocurrencies. The results indicate that all cryptocurrencies generally follow a similar market direction, with a higher probability of being in the 'Down' state. However, there are variations in the probabilities of different cryptocurrencies being in the 'Down' state. This implies that while they share a common market trend, each cryptocurrency is influenced by distinct factors contributing to its individual price fluctuations.

In addition to the diagnostic analysis, we conduct a sensitivity analysis on the constructed BN. This analysis aims to evaluate the relationship between input variables and the target variable by assessing the impact of variations in the input variables on the output variables [11]. The results of the sensitivity analysis, performed using Genie, are presented in Fig. 3b. For

[3] For a node v an ancestor node is a node from which a directed path reaches v.

this analysis, Ripple, designated as a leaf node in the BN, is considered the target node. The primary objective is to identify and rank the cryptocurrencies that exert a significant influence on the price of Ripple. The sensitivity analysis is visually represented, with varying shades of red denoting the strength of influence of each cryptocurrency. The findings reveal that Ripple is sensitive to changes in Bitcoin, Ethereum, and Litecoin, with Litecoin exhibiting a slightly stronger influence. Furthermore, the analysis highlights that Binance Coin and Tether do not exert a substantial influence on Ripple in this specific scenario.

The constructed BN structure offers valuable insights into the distinctions between causal and correlational analyses of cryptocurrencies. One noteworthy observation is the situation of Tether as an isolated node within the BN. This corresponds to its significantly small negative correlation with all other cryptocurrencies, a pattern evident in the correlation matrix. The inclusion of Tether as a stablecoin with limited variations has served two main purposes. Firstly, it aligns with the selection criteria established for choosing cryptocurrencies in this study, ensuring a comprehensive analysis of different types of coins. Secondly, its isolation in the final networks, as expected, validates our approach and provides a better understanding of the cryptocurrency market, thereby supporting the reliability of our findings. Conversely, the correlation matrix indicates robust correlations between Binance Coin and Ethereum (0.95) and between Bitcoin and Ethereum (0.92), which might suggest the existence of edges connecting these cryptocurrencies. However, upon closer examination, the BN reveals a causal relationship only between Bitcoin and Binance Coin, with no causal link established between Bitcoin and Ethereum. Additionally, despite the relatively modest correlation between Ethereum and Litecoin (0.62), the BN exposes a causal relationship between these two cryptocurrencies. This signifies that fluctuations in Ethereum's price influence Litecoin's price. This example underscores the notion that the strength of correlation does not consistently translate into the existence of causal relationships in the cryptocurrency market.

A total of 59 BNs are constructed using the approach detailed in the experimental design section. To assess the relationships between specific pairs of cryptocurrencies, the number of edges connecting them in all 59 BNs is counted. Table 2 summarises the outcomes derived from the proposed approach. In this table, each pair of cryptocurrencies is examined, and the number of edges connecting them, as well as the percentage relative to the 59 networks, is presented. For instance, Binance Coin is the parent of Bitcoin in 25 out of the 59 networks, constituting 42% of the total networks. The last column of the table indicates the total number of times a cryptocurrency acts as the parent of all other nodes. For example, the number 107 in the first row indicates that Binance Coin has been the parent node to other nodes 107 times in total. From the information in the table, it is evident that the most frequent edge occurs between Binance Coin and Bitcoin, as indicated by their 31 edges. Moreover, Binance Coin and Ethereum demonstrate a more substantial influence on other cryptocurrencies, with 107 and 103 edges, respectively, highlighting their roles as parent nodes in all the networks.

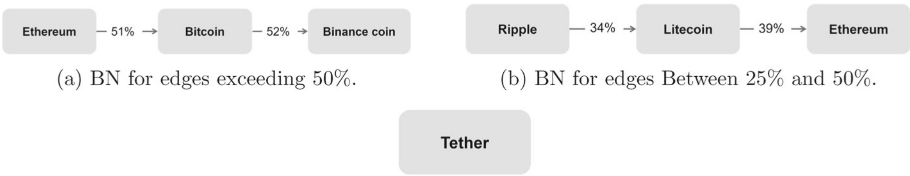
From the information in Table 2, we follow a process guided by two criteria to construct BNs based on the most frequent edges. Firstly, we select the highest value in each row of the table, as highlighted. The highest value in each row implies that a specific cryptocurrency is the parent of the corresponding cryptocurrency more than any other cryptocurrency, potentially indicating the strength of the relationship or the relevance of those two particular nodes. Subsequently, we apply three thresholds to create distinct BNs. Specifically, BNs are created from relationships where the highest values exceed 50%. A threshold above 50% indicates a strong and statistically significant relationship, aiming to capture dominant relationships. Additionally, we also consider thresholds between 25% and 50% and those less than 25% for constructing BNs. The 25–50% range identifies relationships of medium to

Table 2 The number of edges between pairs of cryptocurrencies in all 59 constructed BNs

	Binance Coin	Bitcoin	Ethereum	Litecoin	Ripple	Tether	No. of times being a parent
Binance Coin		**25 (42%)**	22 (37%)	22 (37%)	20 (34%)	18 (30%)	107
Bitcoin	**31 (52%)**		10 (17%)	13 (22%)	13 (22%)	21 (35%)	88
Ethereum	25 (42%)	**30 (51%)**		12 (20%)	20 (34%)	16 (27%)	103
Litecoin	14 (24%)	20 (34%)	**23 (39%)**		5 (8%)	9 (15%)	71
Ripple	13 (22%)	10 (17%)	14 (24%)	**20 (34%)**		12 (20%)	69
Tether	2 (3%)	4 (7%)	5 (8%)	4 (7%)	**11 (19%)**		44

The ‘sum of being parents’ column in the table shows the total number of times a typical cryptocurrency served as the parent of any other cryptocurrencies. The number in parentheses represents the proportional percentage of repeating arcs among all 59 networks

The highest value in each row is in bold and indicates that a specific cryptocurrency is the parent of the corresponding cryptocurrency more frequently



(a) BN for edges exceeding 50%.

(b) BN for edges Between 25% and 50%.

(c) BN with edges less than 25%.

Fig. 4 The BNs constructed based on the various thresholds, where the numbers represent the highest frequency values from Table 2

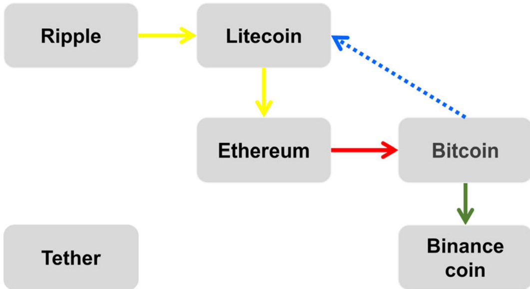


Fig. 5 Comparative analysis of the BNs constructed based on the most frequent edges, considering the thresholds, in Fig. 4, and the BN created from the entire period presented in Fig. 3

strong significance. Finally, a threshold below 25% allows for the inclusion of less prominent but potentially meaningful relationships. The BNs constructed based on Table 2 and two criteria can be seen in Fig. 4. The objective of constructing these BNs is to determine whether a frequently occurring edge between two nodes will persist in the final BN, which is constructed based on the entire dataset (Fig. 3).

Figure 5 provides a comparative analysis of the BNs to investigate whether causal relationships between cryptocurrencies have evolved over time. It compares the BN derived from the entire dataset as presented in Fig. 3 with the BN constructed shown in Fig. 4. In this visual representation, the green arrow is used to denote the edge that is present in both BNs (Fig. 3 and Fig. 4a). Conversely, the red arrow indicates the edge that is among the most frequent ones (Fig. 4a) but are absent in the final BN, which is created from the full dataset. This indicates that the occurrence of frequent edges between coins does not guarantee their presence in the final BN. Moreover, yellow arrows highlight edges that exist in both BNs but with differing directions (Fig. 3 and Fig. 4b). Additionally, dotted blue lines represent an edge that is found only in the final BN (Fig. 3). As we can see, Tether is isolated in both, and there are no edges connected with any other nodes (Fig. 3 and Fig. 4b). These observations underscore that the presence or absence of edges between coins varies during different periods, highlighting the dynamic nature of causal relationships and structural changes in the BNs over time. This variability suggests that cryptocurrency relationships are not static and can evolve, emphasising the importance of considering temporal dynamics when analysing their causal interactions .

5 Conclusions and future directions

This study focuses on the complex relationships among six prominent cryptocurrencies: Bitcoin, Binance Coin, Ethereum, Litecoin, Ripple, and Tether, through the application of BNs. The investigation involves in-depth diagnosis and sensitivity analyses applied to the constructed BN, revealing the substantial influence of Bitcoin and Ethereum over other cryptocurrencies. In contrast, Tether, functioning as a stablecoin, appears to remain largely unaffected by these causal dynamics. Additionally, this study introduces an approach to constructing BNs, enabling an exploration of potential changes in cryptocurrency relationships over time. The analysis reveals that the interconnections among different cryptocurrencies within the BN framework have evolved during the study period. This underscores the dynamic nature of cryptocurrency relationships, emphasising the crucial need for continuous monitoring and analysis in this rapidly changing and complex domain.

Future research can undertake a more comprehensive analysis based on the insights presented in Table 2, enabling a comparative study of BN structures. A particularly promising area involves assessing BNs before, during, and post the COVID-19 pandemic, with a focus on the presence or absence of edges connecting different cryptocurrencies. The comparative examination offers the opportunity to unveil the profound impact of major events, such as the global pandemic, on the dynamics of cryptocurrency relationships. Such insights are invaluable to financial institutions and investors seeking to understand how major events influence the cryptocurrency market. Furthermore, considering the data-driven nature of our BN construction approach, a promising direction for future research is the integration of expert elicitation. Given that the cryptocurrency market is relatively new in comparison to traditional financial markets, the combination of expert opinions with data-driven methodologies can significantly enhance network performance. This approach not only helps in deriving valuable trading strategies but also reduces subjectivity and reliance on extensive data volumes in decision-making. Furthermore, considering the choice of time interval, another direction for future research is the comparison of higher frequencies of data, such as hourly intervals. Utilising different time granularities and comparing outcomes could enhance the robustness of BN models.

Appendix A: augmented Dickey–Fuller test results

This section provides information about the augmented Dickey–Fuller (ADF) test, a unit root test used to assess the stationarity of data. The null hypothesis of the ADF test posits that the time series is non-stationary and possesses a unit root. The alternative hypothesis contradicts this, suggesting the time series is stationary.

The results of the ADF test are shown in Table 3. A value of 0.05 is used as the significance threshold for determining stationarity, where a p value less than 0.05 indicates that the null hypothesis can be rejected, confirming that the time series is stationary. Therefore, based on the p values observed in Table 3, except for Ripple and Tether, the other cryptocurrencies

Table 3 Results of ADF tests for stationarity across various cryptocurrencies, with a significance level set at 0.05

Cryptocurrency	Test Statistic	p-value
Binance coin	−1.594397	0.486407
Bitcoin	−1.405005	0.579874
Ethereum	−1.409285	0.577817
Litecoin	−2.836278	0.053276
Ripple	−4.003867	0.001390
Tether	−5.324708	0.000005

are non-stationary. Consequently, we apply the differencing operator to convert the non-stationary cryptocurrency prices into stationary time series data.

Appendix B: supplementary data

Bayesian Networks
The cryptocurrency Bayesian network model presented in Figure 3 is available at https://doi.org/10.59381/aegpvjkqdt
Data
The data supporting the findings of this study are available in the Git repository at https://github.com/bigrasam/Research-Data.git, providing open access to the research datasets for further investigation and replication

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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