Understanding the Blockchain Interoperability Graph based on Cryptocurrency Price Correlation

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***Abstract*—Cryptocurrencies have gained high popularity in recent years, with over 9000 of them, including major ones such as Bitcoin and Ether. Each cryptocurrency is implemented on one blockchain or over several such networks. Recently, various technologies known as blockchain interoperability have been developed to connect these different blockchains and create an interconnected blockchain ecosystem. This paper aims to provide insights on the blockchain ecosystem and the connection between blockchains that we refer to as the interoperability graph. Our approach is based on the analysis of the correlation between cryptocurrencies implemented over the different blockchains. We examine over 4800 cryptocurrencies implemented on 76 blockchains and their daily prices over a year. This experimental study has potential implications for decentralized finance (DeFi), including portfolio investment strategies and risk management.**

I. Introduction

Cryptocurrencies, with a market capitalization of approximately 2.3 trillion USD as of July 2024 [1], have a high impact on the global economy and offer new investment opportunities [2], [3]. The popularity of Bitcoin [4], established in 2008 with the introduction of blockchain technology, led to the development of this sector. Since then, numerous blockchains have been introduced, serving various functions and supporting their unique cryptocurrencies, such as Ethereum, Polygon, BNB Chain, and Solana. Ethereum [5], recognized as a significant blockchain innovation, introduced smart contracts. These programs operate on the blockchain, consistently maintaining their state during executions.

Smart contracts enable the exchange of cryptocurrencies across various blockchains and their respective implementations on these networks. Numerous mechanisms, typically known as interoperability or cross-chain technologies, have been developed and examined to facilitate inter-blockchain communication [6]–[11]. Blockchain interoperability allows blockchain systems to exchange data, messages, and digital assets with mitigated security risks. This advancement is considered critical for the wide adoption of blockchain technology as it has transformed the blockchain ecosystem from isolated data islands to an interconnected network, allowing joint operation and the exchange of cryptocurrencies across different blockchains.

Our study is motivated by the importance and emergence of blockchain interoperability. We aim to provide insights into the interoperability between major blockchains and the implied blockchain ecosystem as a whole based on such connections.

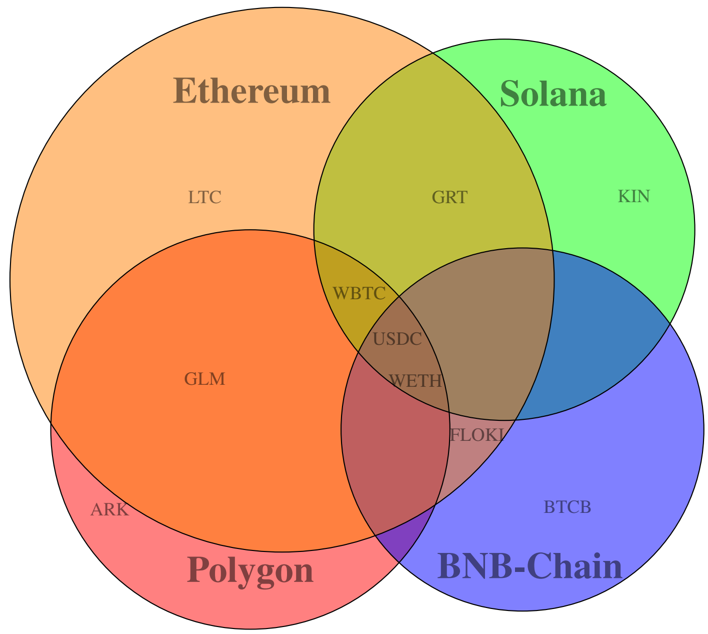


Fig. 1. Venn diagram of four major blockchains Ethereum, Polygon, Binance Smart Chain (BNB-Chain) and Solana with their implemented cryptocurrencies. The cryptocurrencies referred to are Wrapped Bitcoin (WBTC), USD Coin (USDC), Litecoin (LTC), The Graph (GRT), Kin (KIN), Floki Inu (FLOKI), Bitcoin BEP2 (BTCB), Wrapped Ether (WETH), Golem (GLM), and Ark (ARK).

We view the blockchain ecosystem as a graph that we refer to as the *Blockchain Interoperability Graph*. In the graph, nodes represent different blockchains, while edges represent the level of interoperability between a pair of blockchains. We aim to offer insights into the graph by analyzing the correlations between cryptocurrencies implemented across various blockchains.

II. Background

We briefly describe several of the most prominent technologies involved in blockchain interoperability [12]:

Cross-chain bridges are applications that enable the transfer of assets from different blockchains. They can be centralized or decentralized based on the protocol implementation.

Sidechains are secondary blockchains compatible with the main blockchain network. They facilitate communication with the main blockchain using a two-way peg. A two-way peg is a mechanism that facilitates the two-directional movement of assets between the main chain and the sidechain, according to a set or pre-established exchange rate [13].

Wrapped tokens are typically cryptocurrencies that are pegged to the value of another original cryptocurrency or asset, designed for interoperability with different blockchains.

Cross-chain DEXs are decentralized exchanges that enable the exchange of assets between different blockchains.

Cryptocurrencies can have different implementations on several blockchains, which provides compatibility with cross-chain technologies and enables further utilization of cryptocurrencies on each distinct blockchain. Fig. 1 displays various cryptocurrencies implemented across multiple blockchains as detailed on CoinMarketCap [14]. Along the paper, we categorize the cryptocurrencies by their parent blockchain based on CoinMarketCap API [15].

III. Methodology

We model the blockchain ecosystem as the *blockchain interoperability graph*, an (undirected) graph in which nodes represent blockchains. In such a graph, an edge exists between two blockchains upon the existence of an interoperability mechanism between the pair of blockchains that allows the efficient exchange of data and digital assets. The graph can be weighted and in such a case, an edge weight is small if the interoperability mechanism is time efficient, has low cost and low-security risks. In such an ecosystem, two blockchains that are not directly connected can also communicate indirectly through a third blockchain or a path of them, often with higher costs in terms of risks, delay, etc.

Towards understanding the blockchain interoperability graph, we gathered the daily closing prices of 4828 cryptocurrencies from 76 different blockchains for approximately a year, from January 21, 2023, to January 17, 2024, from CoinMarketCap [14]. We aim to provide insights on the blockchain ecosystem by studying the following:

- The correlation between cryptocurrencies implemented on the same parent blockchain compared to the correlation between cryptocurrencies implemented on different parent blockchains.
- The correlation between a pair of blockchains by the correlation of cryptocurrencies for which these blockchains serve as the parent blockchain.

To study the correlation between cryptocurrencies, we use logarithmic return (log return) and Pearson's correlation coefficient as it is widely used [16], [17]. For cryptocurrency i, the closing price on day t is defined as $p_i(t)$. The daily log return, at day t for cryptocurrency i is therefore:

$$R_i(t) = ln\left(\frac{p_i(t)}{p_i(t-1)}\right) = ln(p_i(t)) - ln(p_i(t-1))$$

For a specific timeframe T, R_i represents a vector of log returns. The correlation coefficient (Pearson's correlation coefficient) that measures the correlation between cryptocurrencies i and j over timeframe T is calculated by cross-correlation function. We denote $\sigma_i = \sqrt{E(R_i^2) - E(R_i)^2}$ the standard deviation and $E(\cdot)$ the expected value. We refer to the cross-correlation function as

$$C_{i,j} = \frac{E(R_i R_j) - E(R_i) \cdot E(R_j)}{\sigma_i \cdot \sigma_j}.$$

Note that C is symmetric as $C_{i,j} = C_{j,i}$ and $C_{i,j} \in [-1, 1]$ where -1 indicates maximum anti-correlation, 0 absence of correlation and 1 maximum correlation. We use a metric for Pearson's correlation value based on Evans [18] to measure the correlation strength, as summarized in Table I.

TABLE I
Evan's metric for measuring the strength of Pearson's correlation

Correlation Strength	**Correlation**	**Anti-correlation**
Very weak	0.00 - 0.19	-0.19 - 0.00
Weak	0.20 - 0.39	-0.39 - -0.20
Moderate	0.40 - 0.59	-0.59 - -0.40
Strong	0.60 - 0.79	-0.79 - -0.60
Very strong	0.80 - 1.00	-1.00 - -0.80

To study the correlation between cryptocurrencies, we create an undirected graph in which each cryptocurrency is represented by a node, and the edges indicate the correlation value between the cryptocurrencies. The algorithm for building the graph is described in Algorithm 1. The algorithm receives start date and end date and returns the graph. *cryptoLogReturnVector* is a dictionary where the keys represent the cryptocurrencies, and the values are the corresponding vectors of log returns. *goneByCryptos* are cryptocurrencies whose correlation to the other cryptocurrencies was calculated. *PricesAllCryptos* receives a start date and an end date and returns a dictionary where the keys are the cryptocurrencies, and the values are dictionaries of prices by date. *CalcCorrelation* calculates the Pearson's correlation coefficient based on the cryptocurrencies and the log return vector.

Algorithm 1: Build correlation graph of cryptocurrencies ($startDate, endDate$)

```
Init an empty graph G
Init empty dictionary cryptoLogReturnVector
Init empty goneByCryptos
pricesCryptos = PricesAllCryptos(startDate, endDate)
cryptos = pricesCryptos.keys()
for c ∈ cryptos do
    Add c to goneByCryptos
    if c ∉ cryptoLogReturnVector then
        cryptoLogReturnVector[c] ←
          CalcReturn(startDate, endDate, pricesCryptos, c)
    for c′ ∉ {cryptos \ goneByCryptos} do
        if c′ ∉ cryptoLogReturnVector then
            cryptoLogReturnVector[c′] ←
              CalcReturn(startDate, endDate, pricesCryptos, c′)
        e ← CalcCorrelation(c, c′, cryptoLogReturnVector)
        Add e to G
return G
```

Algorithm 2 receives start date, end date, dictionary of prices per cryptocurrency, and the cryptocurrency. It returns the vector of log return values of the cryptocurrency in the timeframe.

Algorithm 2: $CalcReturn(startDate, endDate, prices, c)$

```
Init empty list returnsList
for from t = startDate + 1 to endDate do
    returnValue ← ln(prices[c][t]) − ln(prices[c][t − 1])
    Add returnValue to returnsList
return returnsList
```

For each cryptocurrency we divide all other cryptocurrencies into two groups:

Group 1: Cryptocurrencies that share the same parent blockchain as the cryptocurrency.

Group 2: Cryptocurrencies with a different parent blockchain as of the cryptocurrency.

An edge that connects a cryptocurrency with another cryptocurrency from group 1 is considered an inner edge, as it connects two cryptocurrencies in the same parent blockchain. An edge connecting a cryptocurrency with another cryptocurrency from group 2 is considered an intersecting edge as it connects two cryptocurrencies implemented on different parent blockchains.

We normalize each cryptocurrency's inner edges correlation values to those of its intersecting edges correlation values. We denote i as the cryptocurrency, B_i the parent blockchain of cryptocurrency i, and τ the threshold. We get the normalized value for the inner edges as *InDominance* and the intersecting edges as *OutDominance* (as a function of τ) as follows:

$$\begin{aligned}
In &= \{(i, j) | j \in B_i, j \neq i\} \\
Out &= \{(i, j) | j \notin B_i\} \\
InHeavy(\tau) &= \{(i, j) | j \in B_i, j \neq i, |C_{i,j}| \geq \tau\} \\
OutHeavy(\tau) &= \{(i, j) | j \notin B_i, |C_{i,j}| \geq \tau\} \\
InHeavyRatio(\tau) &= \frac{|InHeavy(\tau)|}{|In|} \\
OutHeavyRatio(\tau) &= \frac{|OutHeavy(\tau)|}{|Out|} \\
InDominance(\tau) &= \frac{100 \cdot InHeavyRatio(\tau)}{InHeavyRatio(\tau) + OutHeavyRatio(\tau)} \\
OutDominance(\tau) &= 100 - InDominance(\tau)
\end{aligned}$$

We use these measurements in Section IV to provide insights into the relationship between cryptocurrencies from group 1 and group 2.

We measure the correlation between each pair of blockchains based on the correlation of cryptocurrency prices for which these blockchains serve as the parent blockchain. We define $S^{\tau}_{k,m}$ the pairs of cryptocurrencies with a correlation value greater than or equal to τ between blockchains k and m as follows:

$$S^{\tau}_{k,m} = \{(i, j) | i \in B_k, j \in B_m, |C_{i,j}| \geq \tau\}$$

We use $S^{\tau}_{k,m}$ to define the correlation between blockchain k and blockchain m for threshold τ:

$$N^{\tau}_{k,m} = \frac{1}{|S^{\tau}_{k,m}|} \cdot \sum_{(i,j) \in S^{\tau}_{k,m}} C_{i,j}$$

If there are no cryptocurrencies correlated between the blockchains, meaning $S^{\tau}_{k,m} = \emptyset$, then $N^{\tau}_{k,m} = 0$, as we consider the blockchains to be uncorrelated.

To study the blockchain behavior, we use the Minimum Spanning Tree (MST), as it is often the preferred network in financial market analyses [19]–[21]. To employ the MST using the blockchain correlation, we first transform the blockchain correlation matrix N into a distance correlation matrix. We apply the following transformation to create a distance matrix. The distance between blockchains k and m is defined as follows:

$$D^{\tau}_{k,m} = 1 - (N^{\tau}_{k,m})^2$$

where $D^{\tau}_{k,m} \in [0, 1]$ as chosen in [21]. This transformation satisfies an intuitive property where strongly correlated blockchains receive low distance values.

We use the Kruskal algorithm to create the minimum spanning tree (MST) from D to study the blockchains' collective behavior and community structure. We use the Clauset-Newman-Moore community detection algorithm to detect the distinct communities within the MST as shown in Section IV. These communities provide insights into the interoperability graph as they represent groups of correlated blockchains, which are influenced by communication between these blockchains.

IV. Data Analysis

In Table II, we present the 76 blockchains by their total value locked (TVL), number of analyzed cryptocurrencies, and their layer. TVL is a metric that measures the cumulative USD value of digital assets locked or staked on a blockchain via decentralized finance (DeFi) platforms or decentralized applications (dApps). Blockchains with a higher TVL are considered more valuable and secure [22]. Layer 0 blockchains function as infrastructure for other blockchains implemented on top of them. Therefore, we consider their TVL the sum of all other blockchains marked by *. The TVL approximation for each blockchain was taken from [23] in July 2024.

Using correlation data from January 21, 2023, to January 17, 2024, we construct the correlation graph presented in Section III, which serves as the basis for our analysis. We divide this section into two subsections: In subsection IV-A, we demonstrate that cryptocurrencies tend to be more correlated within their parent blockchain. In subsection IV-B, we study the dynamics between blockchains and the interoperability graph through the correlation of the cryptocurrencies implemented on them.

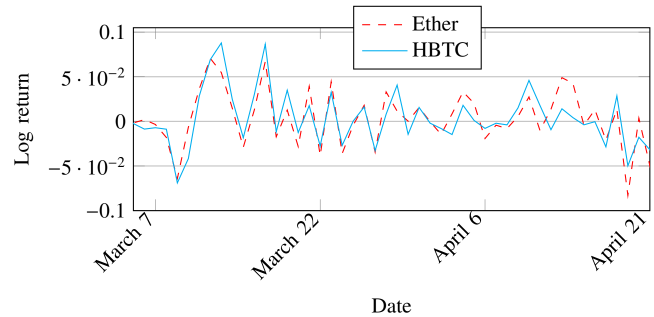
A. Cryptocurrencies correlations

In this subsection, we study the correlation between cryptocurrencies in terms of their parent blockchain implementation. We first demonstrate four different cryptocurrencies and

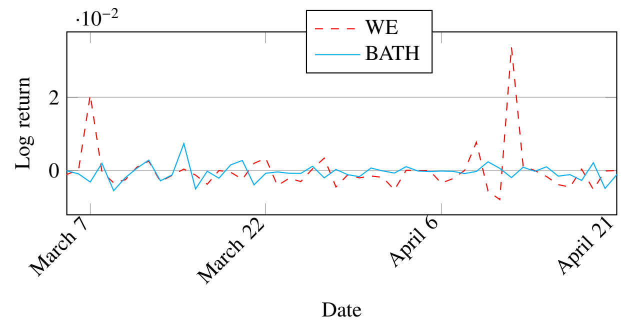
TABLE II

Blockchains statistics (A total of 76 blockchains). Total value locked (TVL) values with refer to aggregated values of blockchains implemented on top of a layer 0 blockchain.

Name	TVL (approximated)	# Coins analyzed	Layer
Bitcoin	$1.053b	1	1
Ethereum	$59.51b	2303	1
BNB	$4.877b	1430	1
Solana	$4.549b	170	1
XRP Ledger	-	14	1
Cardano	$219.36m	24	1
Avalanche C-Chain	-	95	-
Dogechain	$3.05m	5	-
Polkadot	$145m*	2	0
Tron	$7.932b	52	1
Ton	$708.69m	4	1
Polygon	$857.64m	187	2
Bitcoin Cash	$10.95m	2	1
Cosmos	$2b*	2	0
ICP	$67.74m	2	-
Near	$247.64m	9	1
Stellar	$9.6m	11	1
Injective	$53.79m	1	2
Hedera	$71.01m	4	1
Ethereum Classic	$419,049	2	1
Aptos	$355.29m	11	1
VeChain	$608,578	3	1
Cronos	$465.99m	30	1
Optimism	$680.55m	9	2
Stacks	$75.81m	2	-
Elrond	$106.71m	19	1
Algorand	$75.97m	14	1
Fantom	$148.39m	54	1
Theta Network	$2.41m	2	1
Neo	$30.49m	8	1
EOS	$105.01m	8	1
Tezos	$57.52m	11	1
Klaytn	6.61m	48	1
Osmosis	$121.34m	16	-
XDC Network	$7.59m	9	1
Conflux	$14.81m	2	1
IoTeX	$20.46m	5	1
Astar	$26.8m	2	-
Zilliqa	$1.76m	8	1
Nem	-	2	-
Celo	$109.01m	15	1
Waves	$10.42m	8	-
Moonbeam	$39.98m	9	1
Arbitrum	$2.826b	27	2
Harmony	$1.9m	14	-
Ont	$8.89m	2	-
RSK RBTC	-	3	2
Secret	$16.81m	2	1
Elastos	$3.47m	2	-
Everscale	$2.75m	5	1
Viction	$300,770	2	1
Heco	$283,962	19	-
Moonriver	$6.7m	6	1
Fusion network	$102.9m	2	1
Wanchain	$3.86m	4	1
Telos	$38.51m	3	1
Kardiachain	$264,052	3	-
Chiliz	$607,258	44	1
Bitcichain	-	22	-
Arbitrum Nova	$1.77m	1	2
Terra Classic	$2.36m	4	1
Songbird Network	$2.48m	2	1
Althash	-	2	-
Canto	$28.84m	3	1
OKExChain	$2.39m	5	1
Avalanche DFK	-	3	-
Aurora	$9.97m	2	2
Gnosis Chain	$295.57m	5	1
Step	$279,831	2	-
Metis Andromeda	$54.23m	9	2
Fuse	$1.79m	2	1
Oasis Network	$2.12m	3	1
KCC	$1.76m	4	-
Sora	$476,855	3	-
Bitgert	$7,762	2	1
zkSync Era	-	1	2



(a) Log returns of Ether and HBTC over time yield a correlation of 0.8



(b) Log returns of WE and BATH over time yield a correlation of -0.8

Fig. 2. Log returns of four cryptocurrencies: Ether, HBTC, BATCH, and WE by their correlation

their log returns. A positive correlation indicates the same log return behavior, while a negative one indicates anti-correlation behavior, meaning the log return behavior is opposite to one another. We demonstrate very strong and very weak correlations (based on Evans measure) of cryptocurrencies, which we calculate their correlation over the analyzed timeframe (from January 21, 2023, to January 17, 2024). We show their log returns values from March 21, 2023, to April 17, 2023, in Fig. 2. In the paper, we focus on cryptocurrencies with strong and moderate correlations by applying various correlation thresholds in our figures. This approach helps us concentrate on the most relevant cryptocurrencies, as numerous uncorrelated ones do not provide valuable insights into the underlying dynamics of cryptocurrency correlations.

In Fig. 3 and Fig. 4 we show the cumulative distribution function (CDF) of the correlation values of intersecting edges and inner edges per threshold. In Fig. 3, we show that most analyzed cryptocurrencies are not correlated as most have correlation values between -0.1 and 0.2. In Fig. 4, we show that inner edges have higher correlation values in all the strong thresholds, indicating that cryptocurrencies tend to have higher correlation values with cryptocurrencies implemented on the same parent blockchain.

In Fig. 5, we present for various values of the threshold τ, the distribution (over the analyzed cryptocurrencies) of the values of $\mathit{InDominance}(\tau)$ and $\mathit{OutDominance}(\tau)$, as defined in Section III. We aim to provide insights into the correlations of cryptocurrencies both within their parent blockchain and outside of it. Intuitively, the relationship between threshold

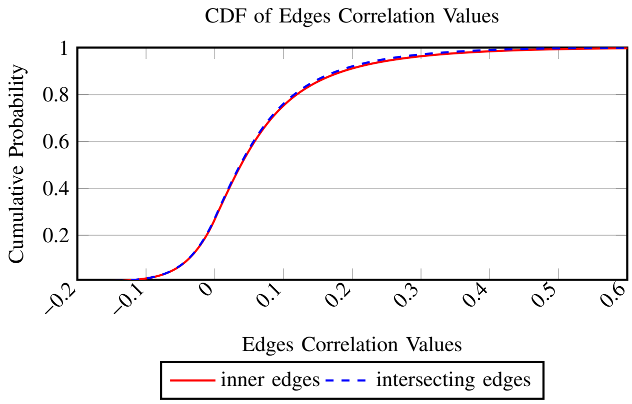


Fig. 3. CDF of inner and intersecting edges correlation values

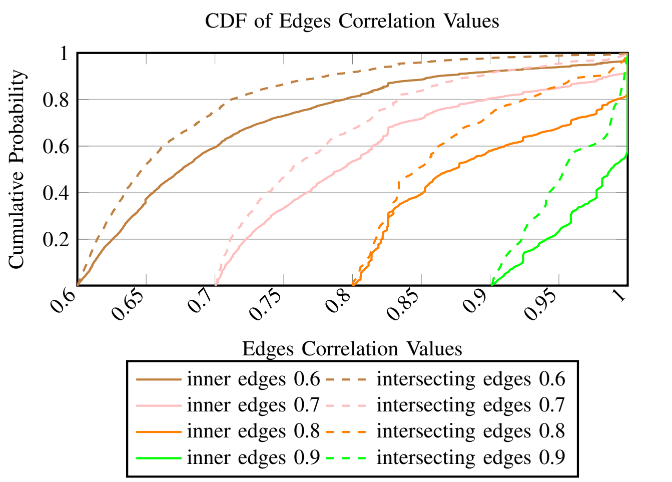


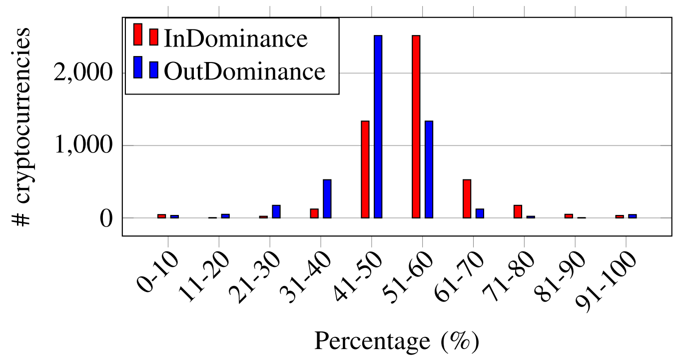
Fig. 4. CDF by threshold of inner and intersecting edges correlation values

values and the two dominance values provides insights on whether belonging to the same parent blockchain impacts the correlation of cryptocurrency prices. Recall that the sum of the two dominance values equals 100.

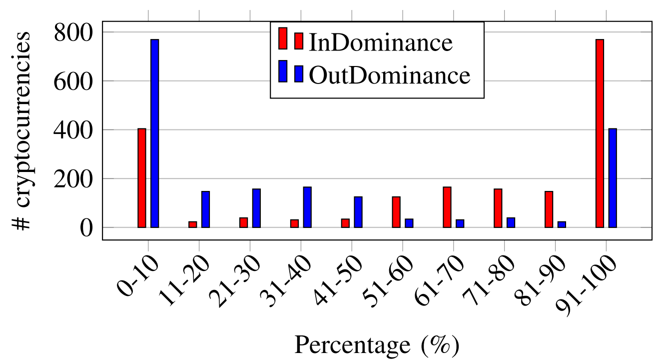
In Fig. 5(a), we show that most cryptocurrencies with a correlation greater than 0.1 tend to have the same correlation to cryptocurrencies implemented on their parent blockchain and cryptocurrencies implemented on other blockchains. This is reasonable as most cryptocurrencies are not correlated to each other, as we showed in Fig. 3; therefore, they do not tend to be correlated to either. For strongly correlated cryptocurrency, we conclude the following from Fig. 5(c) and Fig. 5(d):

- Cryptocurrencies tend to be more correlated within their parent blockchain as their *InDominance* value tends to be higher.
- Most cryptocurrencies with strong correlation tend to be either strongly correlated to the cryptocurrencies implemented on their parent blockchain or cryptocurrencies on other blockchains as most cryptocurrencies' *InDominance* and *OutDominance* values are in the bins 91 – 100 or in bins 0 – 10.

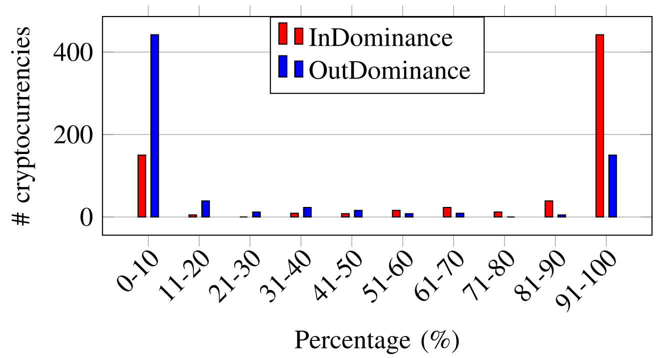
Overall, cryptocurrencies tend to be highly correlated with



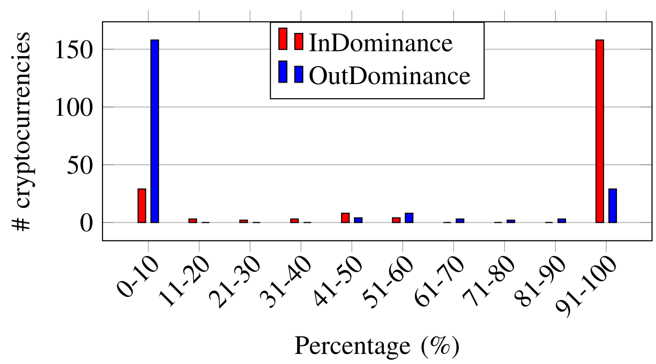
(a) Normalized edges correlation values for threshold $\tau = 0.1$



(b) Normalized edges correlation values for threshold $\tau = 0.5$



(c) Normalized edges correlation values for threshold $\tau = 0.7$



(d) Normalized edges correlation values for threshold $\tau = 0.9$

Fig. 5. Distribution of normalized edges correlation values for various threshold values

cryptocurrencies within their parent blockchain and tend to be either highly correlated to cryptocurrencies implemented on their parent blockchain or to cryptocurrencies implemented on other blockchains.

B. Blockchains Dynamics

In this subsection, we study the blockchain ecosystem based on the correlation between blockchains as formulated in Section III, with threshold value of $\tau = 0.4$ (moderate correlation). We represent the blockchain ecosystem as a graph where a node is a blockchain and an edge represents the correlation between the blockchains. We use the Kruskal and Clauset-Newman-Moore community detection algorithm to study the blockchain communities. We note that we removed Altash from Fig. 6 and Fig. 7 as it was not correlated with any blockchain and therefore did not provide useful information.

We study the structure of communities over several timeframes: from January 21, 2023, to January 17, 2024 (as shown in Fig. 6), from January 21, 2023, to July 18, 2023 (in Fig. 7), and from July 19, 2023, to January 17, 2024 (in Fig. 8). We observe ten communities in Fig. 6, six of which have a central blockchain: Bitcoin, BNB, Harmony, Polkadot, VeChain, and Ethereum. The structure of the communities varies across different timeframes. However, there are key properties that we observe throughout these timeframes.

Bitcoin, Ethereum, and Polkadot are at the center of the communities they induce. This is reasonable because Bitcoin, as the inaugural cryptocurrency, continues to play a pivotal role in influencing the pricing trends across the cryptocurrency market. Ethereum stands out as the most significant blockchain

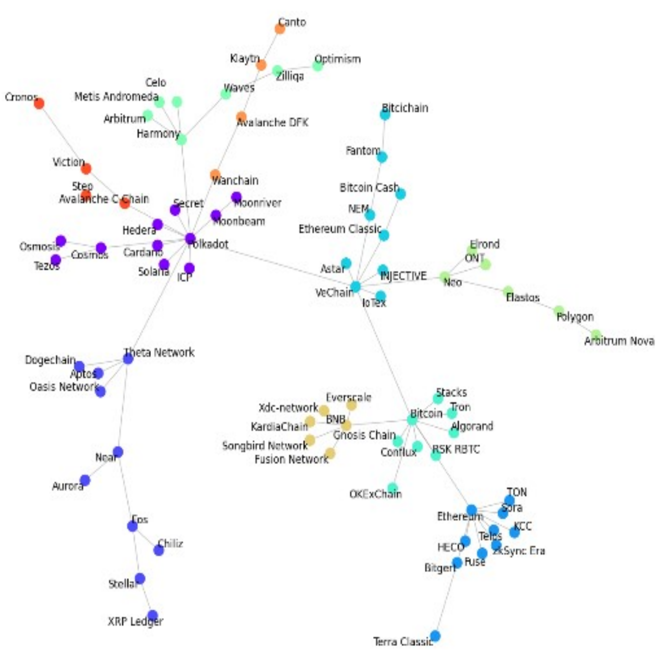


Fig. 6. Minimum spanning tree of blockchains correlation from January 21, 2023, to January 17, 2024.

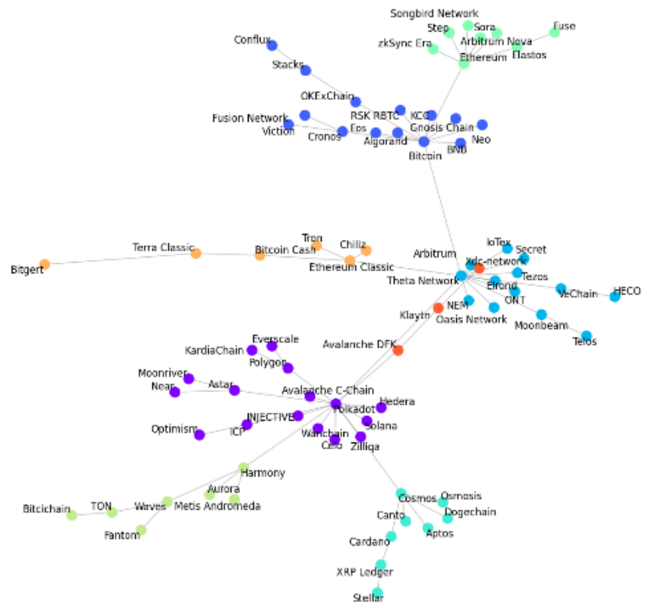


Fig. 7. Minimum spanning tree of blockchains correlation from January 21, 2023, to July 18, 2023

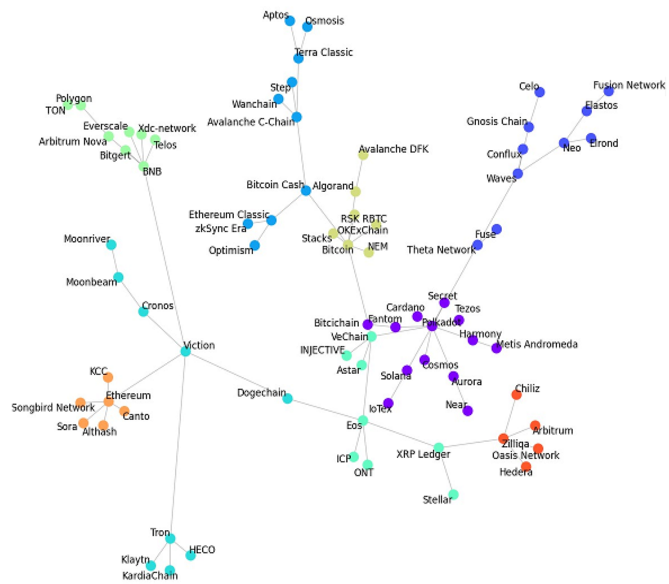


Fig. 8. Minimum spanning tree of blockchains correlation from July 19, 2023, to January 17, 2024

in terms of Total Value Locked (TVL), with the majority of other blockchains maintaining compatibility with its ecosystem. Polkadot is a blockchain protocol designed to connect a multitude of blockchains, facilitating their seamless integration and collective operation on a large scale [24]. We assume that Polkadot's ability to integrate different blockchains potentially enables it to induce its own community. This may signify the future of cross-chain blockchain economic dynamics by introducing cross-chain blockchains that create a more correlated network ecosystem.

We observe that several of Ethereum sidechains (or layer 2 blockchains) such as Polygon and Optimism are not in the same community as Ethereum. This suggests that their properties induce different economic dynamics, causing them to be correlated with other blockchains. The same observation applies to Ethereum Classic and Bitcoin Cash forks, which have diverged with separate economic dynamics from their origin blockchains.

Implementing new technologies to connect different blockchains makes the blockchain ecosystem more interconnected, and accordingly, the interoperability graph is becoming increasingly interconnected. However, the blockchain ecosystem seems to have the form of several communities with an internal relatively high correlation of cryptocurrency prices.

V. Investment implications

Investors can invest in blockchain projects through various means, such as investing capital in application development on a blockchain. Additionally, they can invest in a blockchain by incorporating cryptocurrencies from the same parent blockchain into their portfolios. Our analysis provides several potential implications for investment strategies in blockchains.

Market Forecasting. Investors can leverage the correlation between blockchains to gain market insights, which can aid in predicting conditions like a financial crisis or an economic boom. For instance, the correlation of a number of key blockchains can indicate an economic boom or blockchains that become uncorrelated may signal an impending financial crisis. Analysis of the correlation of blockchains can provide information for investors' strategic decisions.

Risk Management and Diversification. Blockchains with high correlations are likely to react similarly to market fluctuations, potentially resulting in positive or negative performance based on overall market conditions. In contrast, uncorrelated ones are likely to react differently. By understanding these correlations, investors can strategically invest in blockchains to minimize potential losses or maximize revenues. They can invest in different blockchains based on their correlation to diversify their portfolio. This diversification helps stabilize the portfolio's overall performance.

Further work should be done to determine how well our grouping of cryptocurrencies by blockchains and their correlation analysis, impacts portfolios of blockchain investments.

VI. Related Work

To the best of our knowledge, we are the first to study the blockchain ecosystem by the correlation between blockchains. The literature on cryptocurrencies is extensive, given their pivotal role in the blockchain ecosystem.

Dynamics of cryptocurrency prices. Cryptocurrency prices have garnered significant attention in academia from various perspectives, such as predicting cryptocurrency prices [25]–[28], analyzing cryptocurrencies' correlation with other financial assets like gold and fiat currencies [29]–[32], and modeling cryptocurrencies' volatile [33]–[35]. Our study focuses on the correlation among cryptocurrencies, which is significant for investment decision-making process, portfolio management, risk management, and arbitrage [36]–[41].

Correlation of cryptocurrency prices. Several papers have explored the correlation of cryptocurrencies. Such as, Marcin Watorek et al. [42] examine the cryptocurrency market's growth and complexity, comparing it to traditional financial markets. They identify unique characteristics and arbitrage opportunities despite cryptocurrencies' similarities to established markets like the Foreign Exchange Market (Forex). Jiaqi Liang et al. [16] analyze cryptocurrency market risk and dynamics, finding it fragile and unstable despite rapid growth. Correlation matrices and asset trees assess risk, offering investment and regulatory insights. Yongjing Shi et al. [43] apply a multivariate factor stochastic volatility model (MFSVM) to analyze correlations among six major cryptocurrencies, revealing significant positive correlations. They offer insights into the systemic risk of the cryptocurrency market, aiding investment and regulatory decisions.

Vincenzo Candila [44] utilizes the Dynamic Conditional Correlation model and Google search data to examine interconnections among leading cryptocurrencies. He introduces a novel model, the Double Asymmetric GARCH–MIDAS, highlighting the influence of online searches on cryptocurrency volatility, providing key insights for market analysis. Boris Radovanov et al. [45] analyze daily prices of Bitcoin, Ether, Ripple, and Litecoin, revealing their volatility and return patterns using autocorrelation and dynamic models like GARCH. Findings indicate persistent volatility with little asymmetry, offering key insights for cryptocurrency investors and portfolio management. Yunus Karaömer [46] explores the impact of policy uncertainty on cryptocurrency returns using the dynamic conditional correlation (DCC) model, revealing a consistent negative correlation across major cryptocurrencies. This relationship varies with significant events, suggesting that cryptocurrencies might not serve as stable hedges or safe havens during policy uncertainty periods.

VII. Conclusions

In this paper, we introduce the concept of the blockchain interoperability graph to measure the connections between blockchains within the ecosystem. Our analysis is based on the correlation between cryptocurrency prices, which are influenced by the interoperability of the parent blockchains they are implemented on. This analysis focuses on a specific timeframe using a particular methodology, while other potential evaluation methods and timeframes may yield different conclusions. We highlight several key points from our study:

- Strong correlated cryptocurrencies tend to be more correlated to other cryptocurrencies within their parent blockchains.
- The blockchain ecosystem can be interpreted as a community-based graph, where key blockchains such as

Ethereum and Bitcoin are at the center of communities within the graph.
- Blockchains that are forks of their origin blockchains or are sidechains (layer 2) to it tend to form their own economic dynamics.
- Polkadot is an example of a layer 0 blockchain that forms a community, showing the potential effect of the protocol's connectivity on the correlation between blockchains.
- Understanding how blockchains are correlated to each other can offer investment strategies.

Overall, we provide insights on the blockchain ecosystem and the interoperability graph based on the correlation between cryptocurrencies.

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