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Examining Crypto Ecosystem Chains based on Shocks and Responses of Defined Valuation Metrics

Michael Wong Kok Thi[1*]

[1]Trinity Business School, Trinity College Dublin, 182 Pearse St, Dublin 2, D02 F6N2, Ireland. E-mail: miwong@tcd.ie

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Abstract

Using a Vector Autoregressive (VAR) model, this paper investigates the relationships of key performance metrics of crypto ecosystem chains through the analysis of results generated by Impulse Response Functions (IRFs) and Variance Decomposition. Granger Causality test was also used to identify any presence of directional influence to determine causal effects. This study finds that certain cryptocurrencies were able to retain value and maintain their position as ecosystem chains, while others such as Avalanche (AVAX) came into question. Furthermore, matured ecosystems have different behavioral properties as compared to newer additions such as Arbitrium (ARB) and Optimism (OP). Both Total Value Locked (TVL) and Bitcoin (BTC) price possesses strong causality onto other variables investigated, notably in legacy ecosystems; Ethereum (ETH), Binance (BNB), Fantom (FTM). Contrary to popular belief, Trading Volume (V) and Circulating Supply (CS) had little causal impact suggesting a lesser role in predictions of other variables.

Keywords: *Cryptocurrencies, Bitcoin, Market capitalization, Trading volume, Circulating supply, Total value locked, Vector autoregressive model, Variance decomposition, Impulse response function, Granger causality test, Decentralized finance*

1. Introduction

The rapid growth and high volatility of the cryptocurrency market have garnered considerable interest from investors, analysts, and researchers. This dissertation aims to explore the dynamic interactions between key defined performance metrics within certain cryptocurrency ecosystem chains. By focusing on market capitalization, trading volumes, circulating supply, total value locked, and the price of Bitcoin, the study hopes to uncover causality relationships among these variables and their impact on the market behavior. For the study, a quantitative approach was used while also considering certain qualitative aspects. The study employs a Vector Autoregressive (VAR) model, along with Impulse Response Functions (IRFs) and conducting Variance Decomposition analysis. Granger causality tests were used to identify and any presence of directional

* Corresponding author: Michael Wong Kok Thi, Trinity Business School, Trinity College Dublin, 182 Pearse St, Dublin 2, D02 F6N2, Ireland. E-mail: miwong@tcd.ie

influence among these key variables in order to determine causal relationships. Data sets were retrieved from established online crypto databases over periods from 01/04/2023 to 31/05/2024, to ensure robustness and accuracy in the findings. This article contributes to a nuanced understanding of the cryptocurrency market, emphasizing the importance of a comprehensive approach to conduct market analysis on a specific spectrum of classification known as ecosystem chains, and the need for ongoing research to enhance predictive accuracy and investment strategies.

2. Aims and Objectives

2.1. Research Aims and Objectives

This study aims to investigate the dynamic relationships between key performance metrics among selected crypto ecosystem chains. These metrics are Market Capitalization (MC), Trading Volume (V), Circulating Supply (CS), Total Value Locked (TVL) and Bitcoin Price (BTCP). This would be crucial for uncovering dynamic interactions and causal relationships among key metrics across certain prominent cryptocurrencies; Ethereum (ETH), Tron (TRX), Binance Coin (BNB), Solana (SOL), Arbitrum (ARB), Avalanche (AVAX), Polygon (MATIC), Optimism (OP), and Fantom (FTM). By analyzing these relationships through statistical techniques such as a Vector Autoregressive (VAR) model, Impulse Response Functions (IRFs) and variance decomposition, the research seeks to provide a deeper understanding of how shocks from one metric affects the other variables in these cryptocurrency ecosystem chains. Stabilization patterns and confidence intervals of responses to variables shocks would also be investigated to provide insight into market stability and predictability. Granger causality tests would be used to pinpoint directional influences among market capitalization, trading volumes, circulating supply, TVL, and Bitcoin price, identifying any significance within these factors as key indicators for market trends. Moreover, in order to contextualize the findings, the research will review and integrate relevant academic literature, situating the results within the broader scope of cryptocurrency market research. Based on the insights gained, the study intends to offer practical recommendations for investors and analysts, enhancing their strategic decision-making processes. Finally, the research will identify avenues for future exploration, such as incorporating a wider range of cryptocurrencies, integrating qualitative data, and considering external macroeconomic factors, to further deepen the understanding of the complex and evolving cryptocurrency market. Only by understanding the robustness of these crypto ecosystem chains can individuals make better informed decisions in the future.

3. Rationale and Contribution

3.1. Introduction-Status Quo of Research & Description of Topic

Ever since Satoshi Nakamoto published the Bitcoin whitepaper back in 2008, there has been much advancements made in blockchain technology which resulted in remarkable growth for the cryptocurrency market. Blockchain technology has also contributed to growth in other sectors such as Web3.0 and Internet of Things (IoT). This signals a shift towards an economy immersed within the digital space (Murimi *et al.*, 2023). As of today, cryptocurrencies are starting to emerge as a significant financial asset class with a market capitalization exceeding USD$2.5 trillion, attracting global interest from investors, regulators, and scholars. Academics have examined factors influencing cryptocurrency prices, technological advancements and macroeconomic effects. According to studies conducted recently, blockchain technology is being adopted at rapidly, which emphasizes the importance of understanding its effects on the cryptocurrency market (Murimi *et al.*, 2023). In particular, there has been an uptake in the research of Decentralized Finance (DeFi), focusing on technological aspects such as smart contract viability, scalability, tokenization and decentralized autonomous organizations (DAOs). Furthermore, studies on DeFi have examined impacts on Decentralized Exchanges (DEXs), lending, Non-Fungible Tokens NFTs, regulation and traditional finance (TradeFi). Some analysis delves deeper into the reward mechanisms and various risk factors that are associated with these protocols. Despite rapid developments, comprehensive studies which focuses on valuing cryptocurrencies are lacking which could be due to the complex nature of cryptocurrencies. Therefore, there is a need for a study to be conducted on the valuations of crypto ecosystem chains.

3.2. Ecosystem Chains and Decentralized Finance (DeFi)

In recent years, some cryptocurrencies have evolved from being digital assets into vast ecosystems with a diverse range of functions in DeFi such as staking, lending and stablecoin usage to name a few. Ecosystem chains are a classification of cryptocurrencies that enables decentralized applications (dApps) to be built on their platform through the power of smart contracts in the blockchain. Once certain requirements are met, smart contracts are executed automatically without the need for regular human participation. These characteristics coupled with strength in security network attracts Decentralized Finance (DeFi) protocols to be built on chains. Blockchain technology is used in DeFi to provide various financial services ranging from staking, lending, stablecoins, trading while removing the intermediary layer. Blockchain technology utilizes consensus mechanisms, eliminating the intermediaries to allow the storage of data or records in a decentralized manner. Research shows that various industries have been transformed through the enhancement of transparency through the open blockchain ledger, the reduction in costs of transaction, and the improvement of trust among participants (Murimi *et al.*, 2023). The potential of smart contracts is only limited by the creativity of developers to ideate new use cases (Kumar and Amin, 2022). Furthermore, Chiu *et al.* (2022) outlined a theoretical DeFi framework which hints at the potential to revolutionize traditional finance through the power of blockchain. Despite having similar characteristics, each blockchain network is unique which justifies the need for a study to be conducted on these ecosystem chains. To reflect these ecosystems, Ethereum (ETH), Tron (TRX), Binance Coin (BNB), Solana (SOL), Arbitrum (ARB), Avalanche (AVAX), Polygon (MATIC), Optimism (OP), and Fantom (FTM), were selected as they support an array of applications and protocols. The study does not dive into the specific technological advancements and developments of these coins but rather assume a generic classification of these coins under ecosystem chains.

3.3. Applications of DeFi

Cong *et al.* (2019) examined tokenomics, in which how token based platforms in the form of cryptocurrencies operate and generate value for users. Their work displays certain innovative models that have emerged within the cryptocurrency space. One popular application of DeFi is Staking. An automated market maker is when individuals stake their tokens on protocols providing liquidity and security. They receive rewards in the form of interest and additional tokens (Kumar and Amin, 2022). While traditional staking locks up a user's cryptocurrencies for a set time period in order to attain yields, liquid staking enables staking rewards to be earned without the need for the crypto assets to be locked. Typically, users receive a token at a 1:1 rate of the funds deposited in liquid staking protocols. Tokens can be put up as collateral in other DeFi protocols for borrowing purposes or farming yields. This innovative mechanism explains why most funds are deposited in Liquid Staking protocols.

Users can also participate in borrowing or lending programmes. Similar to traditional banking, decentralized lending platforms such as Aave enable participants to pay or earn interest via two forms of lending; secured loans and unsecured flash loans. Firstly, secured loans often require borrowers to pledge collateral (stablecoin or crypto deposits) greater than their borrowed amount. In the event of a default, lenders would be able to redeem the collateral pledged by the borrowers. Unsecured flash loans do not require any guarantee or collateral on the basis that repayments are done atomically through a single block of the underlying blockchain; entire transaction is done within the single block. In the event any part of the transaction deviates from the block, the entire transaction is null and void. This is made possible through smart contract technology (Chiu *et al.*, 2022; Gudgeon *et al.*, 2020; Schär, 2020). DeFi Lending protocols are attractive as individuals can use their crypto holdings as collateral to obtain additional funds to boost their investments. Unfortunately, certain vulnerabilities exist within the DeFi ecosystem, particularly with flash loans which could be exploited for market manipulation (Qin *et al.*, 2020)

Stablecoins, another common function among ecosystem chains, are classified into custodial (custodians holding reserves outside of the chain), and non-custodial (smart contract collateralization of cryptocurrencies and/or stabilization algotrithms) (Klages-Mundt and Minca, 2022). Their work utilized a stochastic model to determine the stability of noncustodial stablecoins, providing insights into certain factors that influences stablecoins performance and reliability. An example of a non-custodial stablecoin is MakerDAO which deploys overcollateralization (100%<) of ETH through Collateralized Debt Positions (CDP) smart contracts. If collateralized positions fall below the threshold, liquidation occurs automatically. Hence the responsibility falls onto the users to maintain sufficient balance in CDP. MakerDAO mints its own stablecoin, DAI, which is USD pegged. In order to maintain the USD peg of DAI, a stability fee is imposed on users. When DAI trades above par (USD$1), stability fees are decreased which encourages borrowing and discourages debt repayments from CDP owners, which increases the supply of DAI (Gadzinski *et al.*, 2023). And if DAI trades below par, borrowers are required to increase their collateralized positions in order to maintain the liquidation ratio. Furthermore, when DAI deviates from the peg, arbitrageurs trade DAI to compensate for movements in demand and supply (Qin *et al.*, 2020). Thus, the stabilization mechanism helps reduce volatility and maintain the peg of DAI.

3.4. Research Gap

While there has been growing number of literatures on cryptocurrencies, there are gaps that still exist in this area. Much work has been done on Bitcoin, blockchain and crypto in terms of technological aspects or trends based on econometrical models. Research has been done in criminal financing and thus, challenges in regulation have had comprehensive studies conducted in areas such as Anti-Money Laundering (AML). Existing research in DeFi has been mainly focused on technological ingenuity and frameworks. However, existing literature in DeFi has been largely fragmented. There has yet to be a study conducted on specific classifications of cryptocurrencies in which their valuations are tested, and their existence challenged. Therefore, this research hopes to bridge the existing gap in understanding ecosystem chain valuations. Through the exploration of relationships between key performance metrics such as market capitalization, circulating supply, trading volume, total value locked and Bitcoin price, this study aims to contribute to the expanding knowledge of digital assets, offering practical insights for readers in the rapidly evolving cryptocurrencies.

4. Literature Review

4.1. Key Valuation Metrics

Metelski and Sobieraj (2022) previously conducted a deep study on Key Performance Indicators (KPIs) in certain DeFi projects and subsequently developing a framework to evaluate the success and potential of these cryptocurrencies. They identified that Total Value Locked (TVL), Protocol Revenue (PR), Total Revenue (TR), Gross Merchandise Volume (GMV) and Inflation Factor (IF) can be used to value the top ranking DeFi protocols at that point in time. Based on gaps identified within existing research, this study aims to build upon the previous study conducted by Metelski and Sobieraj. Rather than having the top ranking DeFi protocols, our study outlines a subcategory of cryptocurrencies known as ecosystem Chains, in which similar performance metrics are applied. This study aims to uncover the relationship between certain key valuation metrics of these ecosystem chains. Expanding on their previous work, our metrics focuses on changes in Market Capitalization (MC), trading Volume (V), Circulating Supply (CS) which reflects inflation, Total Value Locked (TVL) of the cryptocurrencies, and the price of Bitcoin (BTCP). The study believes that these metrics better reflects the valuations of the ecosystem Chains based on the current state and maturity of the market. Relying solely on a specific valuation metric has its limitations as it often leads to an incomplete and skewed perspective of a cryptocurrency. But rather they should be used holistically with other metrics to provide a better and more comprehensive valuation (Corbet *et al.*, 2019). Ultimately, this study looks to determine whether there is any statistical significance to suggest that these performance metrics can provide insight into the valuations of ecosystem chains. Thus, allowing developers, investors, and policymakers to better understand the factors that contribute towards these ecosystem chain valuations and to justify its classification.

4.1.1. Market Capitalization (MC) and Investor Behavior

In traditional finance, market capitalization represents a public company's value as it is calculated by the multiplication of the number of outstanding shares and the price of the share (Praveen and Manoj, 2021). Kumar and Kumara provided analysis on external shocks on market capitalization trends during periods before and after the covid-19 pandemic. On a broader scope, other studies have also documented that companies with larger market capitalization possess greater financial reserves and attracts more investments (Farooq *et al.*, 2022). Due to its simplicity, market capitalization is widely used as a valuation metric for financial analysis and when conducting comparisons between companies. In a similar manner, the market capitalization of a cryptocurrency is derived by multiplying the total number of circulating tokens by the current price of the cryptocurrency. This enables individuals to put a number value on the cryptocurrency. Makridis *et al.* (2023) conducted studies on market capitalizations and investor behaviors, identifying certain factors could that influence market trends. Conversely, Maouchi *et al.* (2022) conducted studies on digital bubbles within NFTs during the covid-19 pandemic, providing insights into the speculative and volatile nature of these cryptocurrency markets. In any case, market capitalization is a key valuation metric in the crypto space which can be used as a proxy for investor behavior in certain circumstances.

4.1.2. Trading Volume (V) – CEX & DEX

After investigating the day of the week effects in cryptocurrency markets, Caporale and Plastun (2019) discovered that trading volume indicates the liquidity of the crypto asset and provides insight into investor sentiment and market activity. This often occurs through changes in price, reflecting demand and supply dynamics. One possibility is that a higher trading volume suggests a growing interest in the chain whereby investors acquire tokens to participate in DeFi such as providing liquidity pools, yield farming and other activities. This results in an increased demand through investor interest and confidence. These actions enhance the functionality and utility of the blockchain which proposes an increased valuation. In a previous study conducted, trading volume could be used to help predict future price movements in individual stocks within the financial markets (Llorente *et al.*, 2002), and therefore there may exist such a relationship in cryptocurrencies. In recent years, trading volumes have risen steady in Centralized Exchanges (CEX) and Decentralized Exchanges (DEX). CEX enables cryptocurrency trading through a centralized platform, such as Binance or Kraken. DEX protocols allow the swapping of cryptocurrency pairings, or execution of transactions from individual private wallets rather than depositing through a centralized custodian. This is made possible through the power of smart contract platforms (Schär, 2020). DEX allows users to have more privacy without the need to undergo KYC or legal identifications through an intermediary custodian. However, transactions still leave digital footprints on the public blockchain. DEXs tend to have lower transactional fees, access to coins that have yet to be launched on CEXs and the freedom to switch to different DEX platforms relatively easily (Makridis *et al.*, 2023). Occasionally, DEXs incentivizes users through governance token airdrops which enables voting rights to decide on the direction of the protocol. Interestingly, a study concluded that airdrops increase the volumes and market capitalizations of the protocol. This implies that users value having a stake in the development of the protocol (Makridis *et al.*, 2023). Also, Chu *et al.* (2023) conducted research on Chain-link, Aave, Maker, Kyber Network and 0x and discovered that there is a positive correlation between the returns and volume. Their work showcases how trading activity can influence movements in the cryptocurrency markets, highlighting trading volume as a critical metric in understanding market dynamics.

As market capitalization is derived by the multiplications of price and circulating supply, volume should affect the valuations of the cryptocurrencies. Unfortunately, trading volume is susceptible towards market manipulation tactics such as wash trading, which occurs when an entity simultaneously executes buying and selling trades to create an illusion of higher trading activity (Gandal *et al.*, 2018). This often results in misleading signals about the crypto's true liquidity and investor interest.

4.1.3. Circulating Supply (CS) – Inflation Rate

Circulating supply displays the number of cryptocurrency tokens that are available in the market, reflecting scarcity and thus, the value of the cryptocurrency in question. For example, akin to traditional fiat, an increase in the circulating supply of a token without a proportional increase in demand dilutes the token supply which often leads to the erosion and depreciation of the value of each token. Conversely, repurchasing and the subsequent burning of tokens can possibly enhance token value through deflationary mechanisms (Li *et al.*, 2021). As different cryptocurrencies have different inflationary mechanisms, the method used by Metelski and Sobieraj was adopted. They determined that changes in the total circulating supply would represent the inflation rate, serving as the counter argument through the erosion of protocol valuations in which tokens are either introduced or removed from the market. This simplifies and standardizes the metric in a relatively fair method for our study on multiple ecosystem chains.

4.1.4. Total Value Locked (TVL) – DeFi Valuation

Total Value Locked (TVL) measures the total value of assets that are locked on the blockchain within various DeFi protocols inclusive of lending, staking and other activities. This reflects the amount of funds that are committed in these smart contract DeFi protocols. Cryptocurrencies with a higher TVL reflects a more functional and vibrant ecosystem, with better user engagement and trust in the blockchain, and hence are perceived as having more value. TVLs only display the current valuations of the deposits themselves. TVL provides insight into the financial relevance of DeFi use and services and would be a viable indicator to assess DeFi protocols (Metelski and Sobieraj, 2022). A previous study conducted by Soiman *et al.* (2022) concluded that DeFis with a high TVL would have a high market capitalization. In a previous study, TVL could be used to determine investor confidence of certain DeFi protocols, and therefore, works as an indicator to monitor the valuation and progress of the DeFi space (Maouchi *et al.*, 2022). In contrast, basing the performance metrics such as high TVLs would not be infallible, with the failing of Terra (LUNA) in 2022, which held the second highest TVL after ETH at that point in time. However, TVLs is not all encompassing as it does not reflect the distribution of assets amongst individual accounts whereby a single account could possibly hold most tokens. Furthermore, potential yields that these deposits would earn are also not reflected, whether it be through staking or liquidity pools. Metelski and Sobieraj also highlighted that different DeFi protocols could be analyzed differently such as the total trading volumes are for DEXs, and total borrowing volume for lending protocols. Revenues from protocols are equal to the distributed revenue to the DeFi token owners, like dividend payouts in TradeFi. Therefore, TVL is a crucial metric in the valuations of ecosystem chains providing insight into the viability of DeFi project.

4.1.5. BTC Price (BTCP) – BTC Dominance and Market Influence

Being the first and most recognizable cryptocurrency, Bitcoin (BTC) continues to exert much influence on the entire crypto market. This phenomenon that is known as Bitcoin dominance, measures BTC's relative market capitalization to the total crypto market capitalization which is 49.93% as of 2nd April 2024 (Coingecko). Studies conducted by Corbet *et al.* (2019) have shown that price fluctuations in Bitcoin often causes corresponding movements in the broader crypto market, which signals directional trends such as investor behavior and market sentiments. However, this metric is not without its limitations. With the influence of macroeconomic factors, market speculation and regulatory news releases, Bitcoin price is highly volatile and susceptible to fluctuations (Cheah and Fry, 2015). This could cause sudden capital shocks into Bitcoin, which can skew valuations instead of providing a complete picture of other DeFi projects and cryptocurrencies (Gandal and Halaburda, 2016). Gandal *et al.* (2018) also studied price manipulation within the Bitcoin ecosystem, providing insights into certain challenges with the integrity of the market. Furthermore, they emphasized the need for robust regulatory frameworks in order to prevent market exploitation. On the other hand, as most trading pairs on CEXs and DEXs are denominated by BTC pairings, one could argue that BTC price movements have significant influence over the valuations of altcoins.

Hence, it is essential to include BTC Price changes alongside other performance metrics to conduct comprehensive market analysis in altcoin valuations. As Bitcoin's own properties have been well documented, this study hopes to extend the part that BTC plays by investigating its influence on these crypto ecosystem chains (Baur *et al.*, 2018; Corbet *et al.*, 2019).

4.2. Contribution of Research

The emergence of cryptocurrencies has disrupted the financial landscape by providing an alternative investment opportunity to traditional finance (TradeFi). Often, people tend to argue that crypto is just speculation and a bubble likened to the dot.com bubble crash. However, while some online companies filed for bankruptcy, there were companies that survived and became integral into the technological space today such as Microsoft, Amazon and Cisco to name a few. Hence, there is a need to develop and refine methodologies to filter for cryptocurrencies that provides a value proposition for the longer term. Furthermore, for alternative coins to gain a foothold in the crypto space, dependency on Bitcoin (BTC) price movements needs to be decreased and definitive individual valuations are required.

Therefore, there is a need for a study to be conducted on these cryptocurrencies to demystify the illusion on whether they can be classified as ecosystem chains through the retention of value. Moreover, the study attempts to discover any presence of hypothesized directions of causality between variables. Ultimately, the study would contribute towards the growing repository of literature in cryptocurrencies with a specific take on ecosystem chains.

5. Methodology

5.1. Research Model

The study aims to investigate how the various metrics relate to one another overtime using a Vector Autoregressive (VAR) model, accompanied by Impulse Response Functions (IRFs) and Variance Decomposition. For the study, quantitative multivariate analysis would be conducted on multiple time series variables to investigate for any presence of simultaneous interactions between variables. The VAR model would incorporate p time lags which accounts for temporal dependencies. Subsequently, Impulse Response Functions (IRFs) would be used to investigate the effects of shocks. Finally, Variance Decomposition was conducted to isolate the explanatory variables. These empirical analyses were executed with the statistical programme Stata 18 MP.

5.1.1. Data Collection and Selection Criteria

For the study, a quantitative approach was used for the analysis, substantiated by previous existing qualitative literature. The examination of academic literature was done systematically by going through reputable journals. Certain keywords such as cryptocurrencies, DeFi, Bitcoin were used to optimize the repository search. Academic literature was collected from 2015 onwards in order to maintain recency with the cryptocurrency markets. These studies would provide certain definitions and allow the research to gain a foothold in grasping the status quo on cryptocurrencies. As certain specific statistical techniques were lacking in existing crypto research papers, methodological studies on other topics were retrieved to provide a better understanding on how to proceed with my research. For example, IRFs, variance decomposition and endogeneity concerns were areas in which cryptocurrency research were lacking. These additional research papers collected dated back to 2002.

Noting that cryptocurrencies are volatile in nature, high-frequency daily data was collected for the following 9 cryptocurrencies: Ethereum (ETH), Tron (TRX), Binance Coin (BNB), Solana (SOL), Arbitrum (ARB), Avalanche (AVAX), Polygon (MATIC), Optimism (OP), and Fantom (FTM). These cryptocurrencies were selected were based on data availability and their relevance towards the specific criterions. Firstly, the number of protocols that currently exists on the chain should exceed 100 as it indicates a sufficient activity on the blockchain reflecting the maturity of the ecosystem. Next, the cryptocurrency should be ranked among the top 100 cryptocurrencies based on the market capitalization (coinmarketcap and coingecko), as it reflects the sufficient interest and investment in the chain. Lastly, the cryptocurrency should have been listed on major exchanges before 2024 to ensure that there is enough historical data for analysis. These selection criteria's would differentiate matured crypto ecosystems which establishes a better and more meaningful context for analysis. Our study focused on the following individual cryptocurrency data sets for each which includes market capitalization, volume, circulating supply and Bitcoin price. Data on these variables were extracted on 2nd June 2024; SGT 1.45 a.m., from Coingecko (coingecko.com); a public repository that aggregates crypto data from 1,110 exchanges as of (2nd June 2024). Daily TVL data for DeFi protocols were collected from Defillama (defillama.com) accessed on 2nd June 2024; SGT 1.45 a.m. Defillama was chosen as it is one of the most comprehensive DeFi data aggregators that collects and displays extensive metrics and financial data for the various DeFi protocols.

5.1.2. Time Period

Noting that Arbitrium was listed on major exchanges (Binance) on 23/03/2023, our data period began on the 1st of April, whereby a buffer time of a week was allocated to allow ARB to stabilize in terms of its trading activity, which reduced initial anomalous outliers within its price, volume and market capitalizations. The time period ends on the 31st of May 2024, shortly after the US Securities Exchange Commission (SEC) approved proposals for spot Ethereum ETFs in the US (CNBC). Therefore, the study spans from 01/04/2023 to 31/05/2024.

5.1.3. Data Pre- Processing

Initially, data processing included standardized log functions. After testing for stationarity with Augmented Dickey Fuller (ADF) tests, certain variables required an additional step of first order differentials. Unfortunately, the VAR model faced issues in which the Granger Causality Test produced some invalid results whereby the degree of freedom (df) was 0. This implied that there were possible errors made. Upon re-checking the steps and the variance inflation factor tests in which no issues were found, an alternative approach with percentages was used which would be outlined below.

Since the study is investigating multiple cryptocurrencies with large differences in absolute nominal terms, there is a need to normalize the data. During data pre-processing, nominal values were converted into percentage change in a similar manner like Caporale and Plastun (2019), allowing a more consistent analysis as terms are now denominated in a similar scale. Furthermore, this also removed the need to use logarithmic functions, reducing the complexity of our model.

$$Percentage\ Change = \left(\frac{X_t}{X_{t-1}} - 1\right) \times 100\%$$

Where by X_t is the value at time t, and X_{t-1} is the value at time $t - 1$ (previous day).

5.2. Unit Root Stationary Tests

The augmented Dickey-Fuller (ADF) test was used to ensure stationarity through unit roots. As the ADF would have type one errors, an alternative stationary test Phillips–Perron (PPerron) test was also be performed to add an additional layer of confirmation to proceed. Both the ADF and PPerron tests gave approximate p-value for $Z(t) = 0.0000$, implying that these data sets are stationary. This meant that the initial transformation during the data pre-processing had converted our non-stationary into stationary data, hence removing the need for first order differentials. In addition, the data points were also plotted graphically as a second layer visual check for stationarity. As can be seen from Figures 1 to 5, except for the presence of certain outlier data points, all the variables are stationary during the time period investigated. Moreover, cointegration tests were not required to be performed as all our data sets are stationary (Shrestha and Bhatta, 2018).

5.3. Autocorrelation and Multicollinearity Test

Next, an initial regression was conducted as a temporary placeholder model to enable correlation, Variance Inflation Factor (VIF) and Durbin Watson Test to be performed. This pre-emptively helps to detect if any variable estimations are inflated (Shrestha and Bhatta, 2018). Across the cryptocurrencies, Total Value Locked (TVL) and Bitcoin Price (BTCP) have high correlations with Market Capitalizations (MC). Most cryptocurrencies have negative correlations between MC and CS, TVL and CS, which logically accounts for inflationary pressures eroding value. Interestingly, Circulating Supply (CS) have the highest positive correlation with MC in ARB and OP, along with ETH, TRX, SOL, AVAX, MATIC also having positive correlations. Only SOL has negative correlations between their TVL and CS. Except for AVAX, most cryptocurrencies also have significant correlations between TVL and BTCP. Variance Inflation Factor (VIF) tests were performed to check for the presence of any multicollinearity issues. As the tests reveal that VIFs were relatively low (< 2), this reduced the

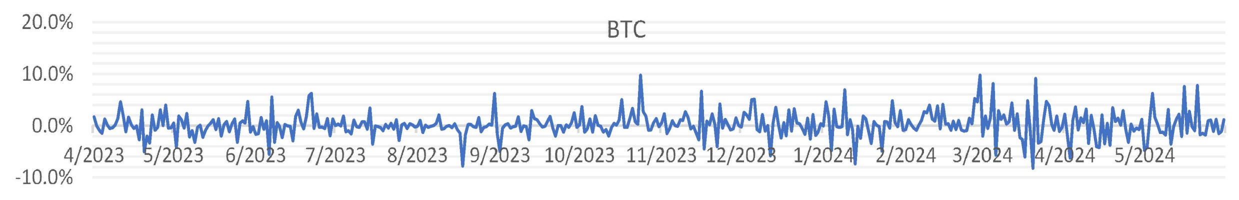

Figure 1: Daily % Change of Bitcoin Price from 01/04/2023 to 31/05/2024

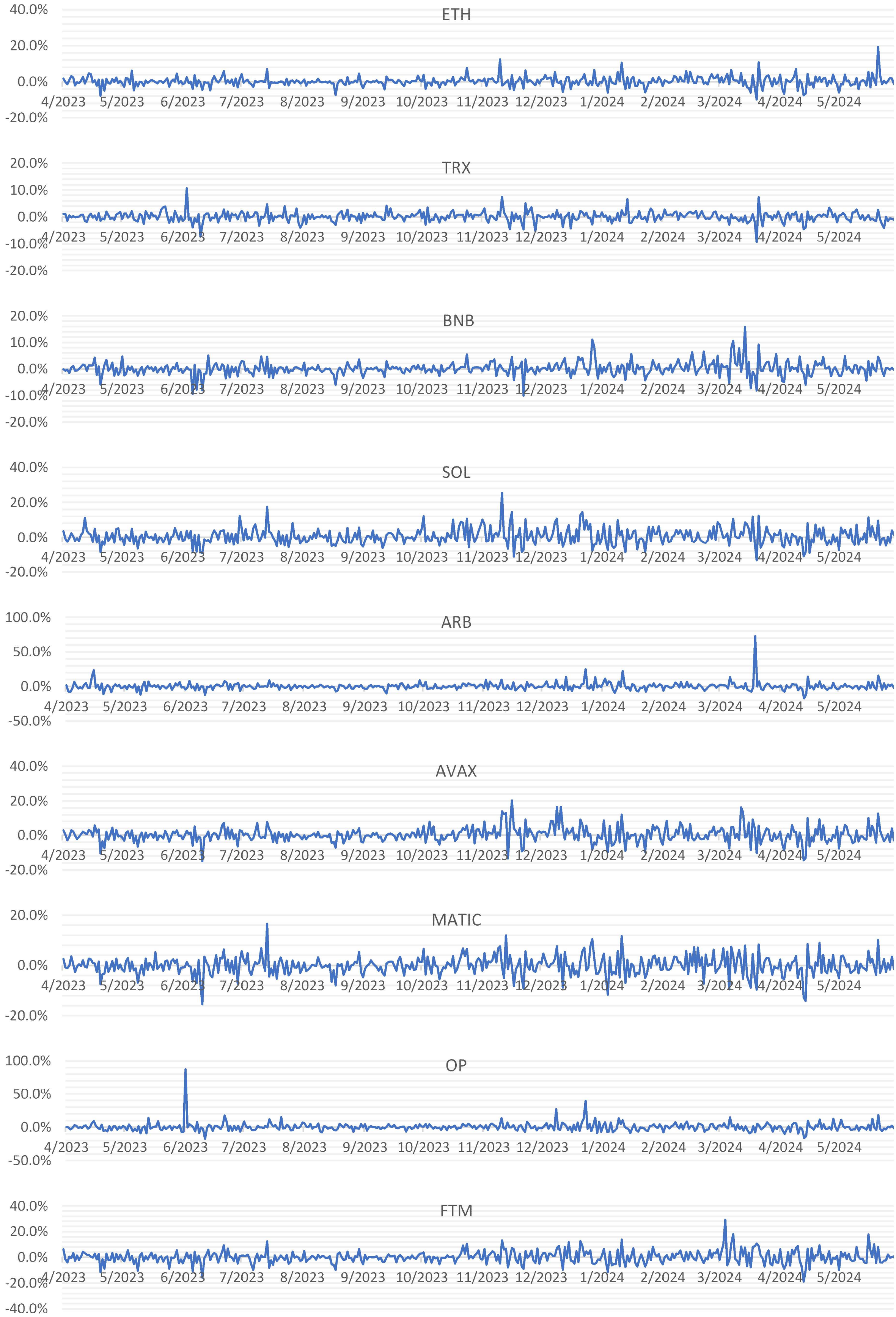

Figure 2: Daily % Change of Market Capitalization from 01/04/2023 to 31/05/2024

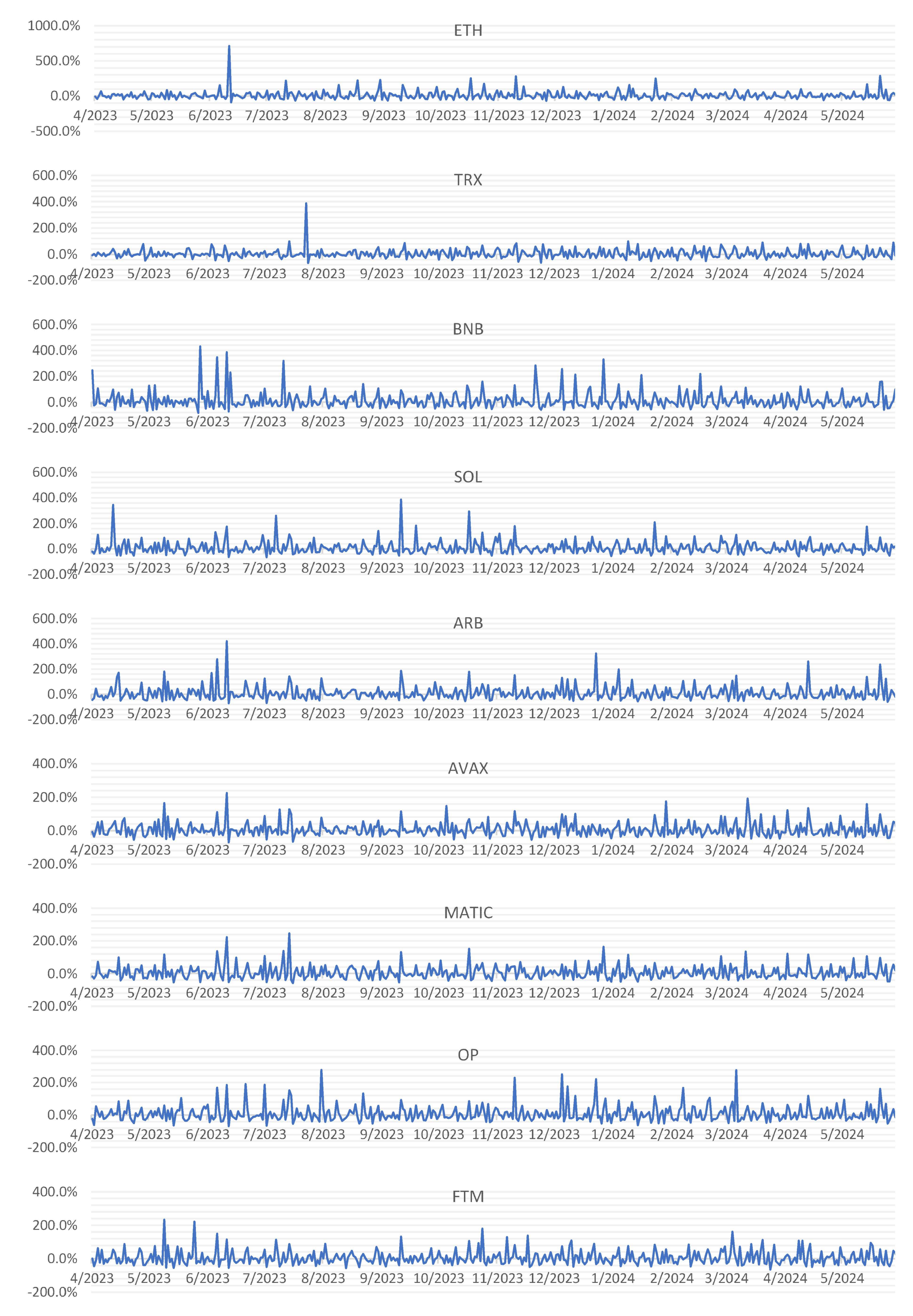

Figure 3: Daily % Change of Trading Volume from 01/04/2023 to 31/05/2024

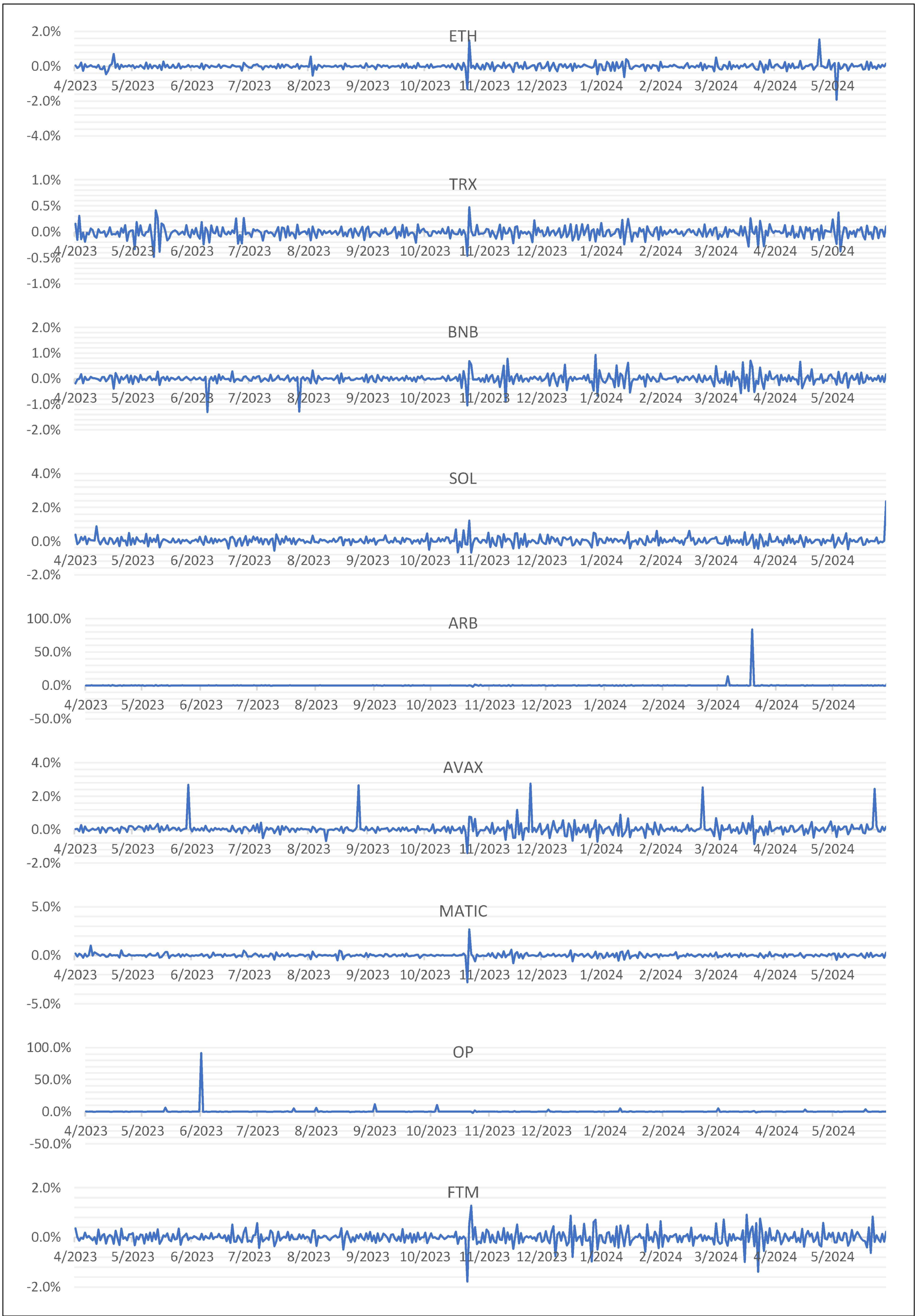

Figure 4: Daily % Change of Circulating Supply from 01/04/2023 to 31/05/2024

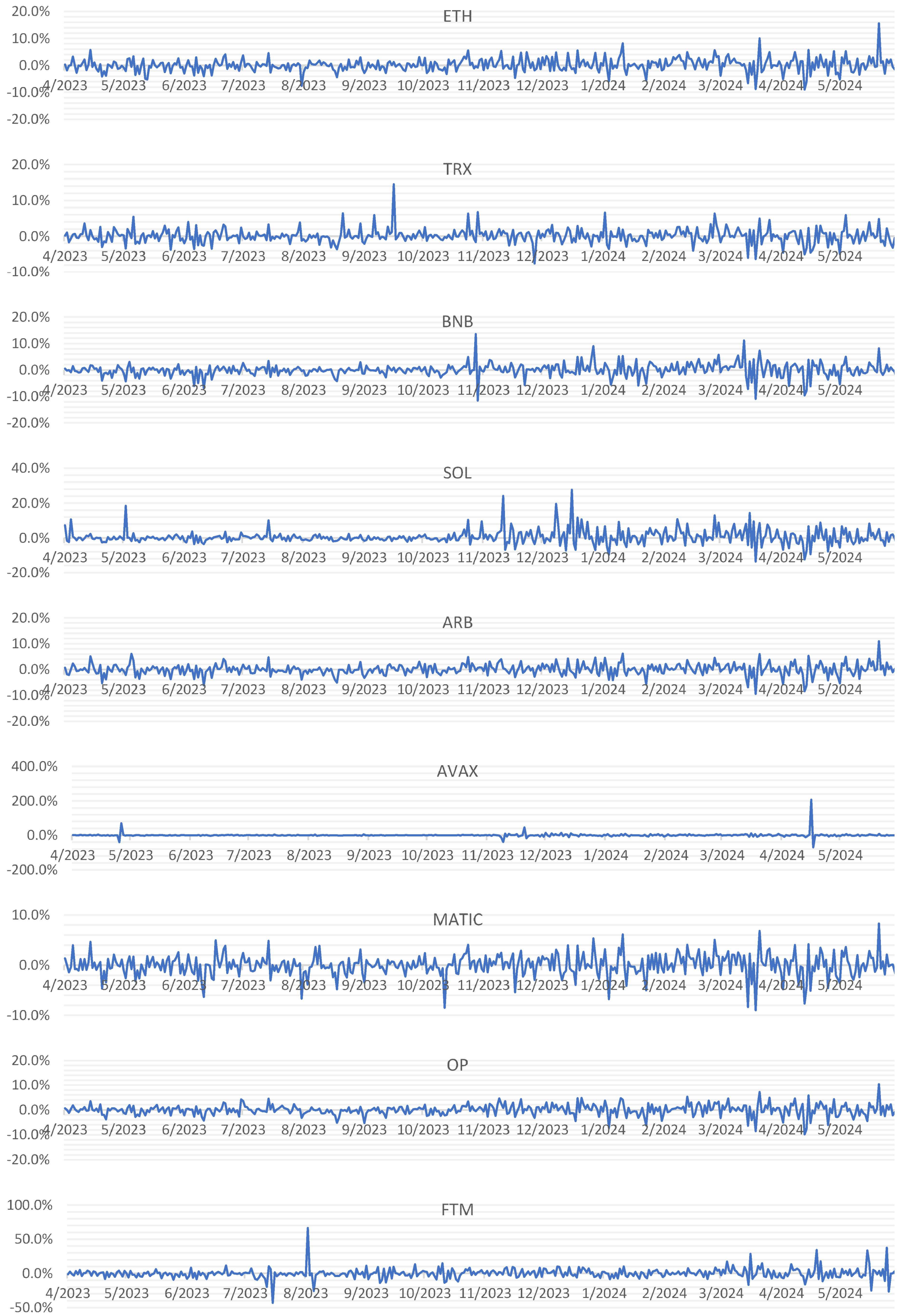

Figure 5: Daily % Change of Total Value Locked from 01/04/2023 to 31/05/2024

likelihood of multicollinearity interfering with potential results later. Durbin Watson (DW) tests were used to detect if there was any presence of autocorrelations in residuals. As the DW test results tended towards 2, the variables would have a lower likelihood of having autocorrelations within models. As autocorrelation and multicollinearity were largely absent, this allowed the study to proceed with the selected variables with better reliability and reassurance of the data sets. Test results are outlined within Figure 6 below.

Matrix of Correlations | **Variance Inflation Factor wrt MC** | **Durbin Watson Test**

Variables	(1) pETHMC	(2) pETHV	(3) pETHCS	(4) pETHTVL	(5) pBTCP
(1) pETHMC	1.000				
(2) pETHV	0.125	1.000			
(3) pETHCS	0.035	0.022	1.000		
(4) pETHTVL	0.771	0.029	-0.034	1.000	
(5) pBTCP	0.787	0.077	-0.022	0.659	1.000

	VIF	1/VIF
pBTCP	1.780	0.562
pETHTVL	1.772	0.564
pETHV	1.007	0.993
pETHCS	1.002	0.998
Mean VIF	1.390	.

ETH
2.185

Variables	(1) pTRXMC	(2) pTRXV	(3) pTRXCS	(4) pTRXTVL	(5) pBTCP
(1) pTRXMC	1.000				
(2) pTRXV	0.115	1.000			
(3) pTRXCS	0.049	-0.027	1.000		
(4) pTRXTVL	0.390	0.040	-0.029	1.000	
(5) pBTCP	0.458	0.068	-0.012	0.603	1.000

	VIF	1/VIF
pBTCP	1.575	0.635
pTRXTVL	1.571	0.636
pTRXV	1.005	0.995
pTRXCS	1.002	0.998
Mean VIF	1.288	.

TRX
1.906

Variables	(1) pBNBMC	(2) pBNBV	(3) pBNBCS	(4) pBNBTVL	(5) pBTCP
(1) pBNBMC	1.000				
(2) pBNBV	0.093	1.000			
(3) pBNBCS	-0.146	-0.030	1.000		
(4) pBNBTVL	0.429	-0.020	-0.127	1.000	
(5) pBTCP	0.565	-0.034	-0.078	0.443	1.000

	VIF	1/VIF
pBNBTVL	1.258	0.795
pBTCP	1.246	0.802
pBNBCS	1.018	0.982
pBNBV	1.002	0.998
Mean VIF	1.131	.

BNB
1.804

Variables	(1) pSOLMC	(2) pSOLV	(3) pSOLCS	(4) pSOLTVL	(5) pBTCP
(1) pSOLMC	1.000				
(2) pSOLV	0.173	1.000			
(3) pSOLCS	0.059	0.146	1.000		
(4) pSOLTVL	0.574	0.111	0.060	1.000	
(5) pBTCP	0.634	0.077	-0.018	0.358	1.000

	VIF	1/VIF
pSOLTVL	1.161	0.862
pBTCP	1.152	0.868
pSOLV	1.035	0.966
pSOLCS	1.026	0.975
Mean VIF	1.093	.

SOL
1.847

Variables	(1) pARBMC	(2) pARBV	(3) pARBCS	(4) pARBTVL	(5) pBTCP
(1) pARBMC	1.000				
(2) pARBV	0.194	1.000			
(3) pARBCS	0.622	0.022	1.000		
(4) pARBTVL	0.318	-0.041	-0.214	1.000	
(5) pBTCP	0.384	-0.005	-0.044	0.597	1.000

	VIF	1/VIF
pARBTVL	1.647	0.607
pBTCP	1.573	0.636
pARBCS	1.060	0.943
pARBV	1.002	0.998
Mean VIF	1.321	.

ARB
2.154

Variables	(1) pAVAXMC	(2) pAVAXV	(3) pAVAXCS	(4) pAVAXTVL	(5) pBTCP
(1) pAVAXMC	1.000				
(2) pAVAXV	0.132	1.000			
(3) pAVAXCS	0.012	0.007	1.000		
(4) pAVAXTVL	0.097	-0.015	-0.047	1.000	
(5) pBTCP	0.613	0.028	-0.082	0.070	1.000

	VIF	1/VIF
pBTCP	1.012	0.988
pAVAXCS	1.009	0.991
pAVAXTVL	1.007	0.993
pAVAXV	1.001	0.999
Mean VIF	1.007	.

AVAX
1.635

Variables	(1) pMATICMC	(2) pMATICV	(3) pMATICCS	(4) pMATICTVL	(5) pBTCP
(1) pMATICMC	1.000				
(2) pMATICV	0.064	1.000			
(3) pMATICCS	0.010	0.017	1.000		
(4) pMATICTVL	0.647	-0.002	-0.028	1.000	
(5) pBTCP	0.617	0.025	0.036	0.593	1.000

	VIF	1/VIF
pBTCP	1.551	0.645
pMATICTVL	1.549	0.646
pMATICCS	1.005	0.995
pMATICV	1.001	0.999
Mean VIF	1.277	.

MATIC
2.175

Variables	(1) pOPMC	(2) pOPV	(3) pOPCS	(4) pOPTVL	(5) pBTCP
(1) pOPMC	1.000				
(2) pOPV	0.329	1.000			
(3) pOPCS	0.637	0.059	1.000		
(4) pOPTVL	0.312	-0.028	-0.075	1.000	
(5) pBTCP	0.275	-0.012	-0.052	0.564	1.000

	VIF	1/VIF
pOPTVL	1.471	0.680
pBTCP	1.466	0.682
pOPCS	1.009	0.991
pOPV	1.004	0.996
Mean VIF	1.238	.

OP
2.194

Variables	(1) pFTMMC	(2) pFTMV	(3) pFTMCS	(4) pFTMTVL	(5) pBTCP
(1) pFTMMC	1.000				
(2) pFTMV	0.179	1.000			
(3) pFTMCS	-0.080	0.017	1.000		
(4) pFTMTVL	0.347	0.023	-0.091	1.000	
(5) pBTCP	0.555	0.013	-0.043	0.250	1.000

	VIF	1/VIF
pFTMTVL	1.074	0.931
pBTCP	1.067	0.937
pFTMCS	1.009	0.991
pFTMV	1.001	0.999
Mean VIF	1.038	.

FTM
1.956

Figure 6: Correlations, Variance Inflation Factor, Durbin Watson Tests

5.4. VAR Model Selection

As the variables are multivariate time series, VAR analysis would be conducted first, subsequently impulse response functions are generated and investigated along with variance decomposition.

5.5. Optimal Lag Pre-Estimation

As the study is concerned with investigating the dynamic relationships between variables through shocks, the Vector Autoregressive Model (VAR) methodology presented by Shrestha and Bhatta (2018) was adopted to obtain unbiased estimations. A previous study reminds us that endogeneity can be a cause for concern, which may leave us with spurious results. Hence, careful consideration of the lag length is essential to the integrity of the VAR model (Abdallah *et al.*, 2015). Pre-estimation for the VAR model assumed 1 week, which correlates to 7 days, and hence, 7 lags as the maximum number of lags. This would be a sufficient lag number when estimating the VAR model as Crypto markets move quickly and would be receptive to shocks within a week. As our sample size is large with 420 recorded observations, the Likelihood Ratio (LR) test estimates the VAR model with reduced lags. Subsequently, optimal lags would be selected through Akaike Information Criterion (AIC), Schwartz Bayesian Criterion (SBC) and Hannan Quinn criterion (HQIC) based on the highest frequency and lowest denoted lag number (Shrestha and Bhatta, 2018). When these tests suggest an optimal lag of 0, an optimal lag of 1 was selected instead, otherwise it would be difficult to determine any relationships between these variables overtime. If 2 or more lags were used, both immediate and delayed responses could be captured by IRFSs, which could overcomplicate and cloud the results making it harder to isolate and interpret. As most of the models indicated an optimal lag number of 1 (Appendix A), the study proceeded with an optimal lag of 1 for all respective cryptocurrencies. This standardizes the investigation while prioritizing simplicity and avoided overfitting. Nevertheless, the study acknowledges its limitations in capturing more detailed dynamics. This approach would improve the reliability and robustness of the VAR models for better comparative analysis (please refer to Appendix A).

5.6. Econometric VAR Model

With an optimal lag of 1, the percentage change p of the variables at time t is modelled as a function of both its own and other performance metrics' past values. The VAR model records the interdependencies among the variables which enables us to investigate how each variable is affected by shocks of other variables overtime.

(1)	$p(CryptoMC_t) = \alpha_\theta + \beta_1 p(CryptoV_{t-1}) + \beta_2 p(CryptoCS_{t-1}) + \beta_3 p(CryptoTVL_{t-1}) + \beta_4 p(BTCP_{t-1}) + \varepsilon_t$
(2)	$p(CryptoV_t) = \alpha_\theta + \beta_1 p(CryptoMC_{t-1}) + \beta_2 p(CryptoCS_{t-1}) + \beta_3 p(CryptoTVL_{t-1}) + \beta_4 p(BTCP_{t-1}) + \varepsilon_t$
(3)	$p(CryptoCS_t) = \alpha_\theta + \beta_1 p(CryptoMC_{t-1}) + \beta_2 p(CryptoV_{t-1}) + \beta_3 p(CryptoTVL_{t-1}) + \beta_4 p(BTCP_{t-1}) + \varepsilon_t$
(4)	$p(CryptoTVL_t) = \alpha_\theta + \beta_1 p(CryptoMC_{t-1}) + \beta_2 p(CryptoV_{t-1}) + \beta_3 p(CryptoCS_{t-1}) + \beta_4 p(BTCP_{t-1}) + \varepsilon_t$
(5)	$p(BTCP_t) = \alpha_\theta + \beta_1 p(CryptoMC_{t-1}) + \beta_2 p(CryptoV_{t-1}) + \beta_3 p(CryptoCS_{t-1}) + \beta_4 p(CryptoTVL_{t-1}) + \varepsilon_t$

$$\begin{pmatrix} p(CryptoMC_t) \\ p(CryptoV_t) \\ p(CryptoCS_t) \\ p(CryptoTVL_t) \\ p(BTCP_t) \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \end{pmatrix} + \begin{pmatrix} \beta_{1,1} & \beta_{1,2} & \beta_{1,3} & \beta_{1,4} & \beta_{1,5} \\ \beta_{2,1} & \beta_{2,2} & \beta_{2,3} & \beta_{2,4} & \beta_{2,5} \\ \beta_{3,1} & \beta_{3,2} & \beta_{3,3} & \beta_{3,4} & \beta_{3,5} \\ \beta_{4,1} & \beta_{4,2} & \beta_{4,3} & \beta_{4,4} & \beta_{4,5} \\ \beta_{5,1} & \beta_{5,2} & \beta_{5,3} & \beta_{5,4} & \beta_{5,5} \end{pmatrix} \begin{pmatrix} p(CryptoMC_{t-1}) \\ p(CryptoV_{t-1}) \\ p(CryptoCS_{t-1}) \\ p(CryptoTVL_{t-1}) \\ p(BTCP_{t-1}) \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \varepsilon_t \\ \varepsilon_t \\ \varepsilon_t \\ \varepsilon_t \end{pmatrix}$$

Figure 7: VAR Model Matrix Equation for Crypto Valuation Metrics

The is better represented through a matrix equation (Figure 7) which showcases all five variables; market capitalization (CryptoMC), volume (CryptoV), circulating supply (CryptoCS), total value locked (CryptoTVL), and Bitcoin price (BTCP). The percentage change of each variable is represented as p, and time t is the base period and t–1 is the first lag order. α_1 represents the intercept term for the i^{th} equation, $\beta_{i,j}$ represents the various coefficient for the i^{th} equation with the j^{th} variable and ε_t represents the error terms capturing all unexplained variations in the function for the t period.

In each of the cryptocurrencies, the fit of the VAR model was investigated. Goodness of fit tests in the form of RMSE and R^2 can be used to examine how well the data is explained by the regression. Root Mean Square Error (RMSE) captures predicted values of the VAR model and actual values. Hence, a lower RMSE implies that the

ETH Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	4997.192	AIC	=	-23.32015
FPE	=	5.13E-17	HQIC	=	-23.20736
Det(Sigma_ml)	=	4.45E-17	SBIC	=	-23.03462

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pETHMC	6	0.025691	0.1460	72.85696	0.0000
pETHV	6	0.627744	0.0177	7.678222	0.1749
pETHCS	6	0.001953	0.1448	72.15244	0.0000
pETHTVL	6	0.024183	0.0445	19.8251	0.0013
pBTCP	6	0.023084	0.1045	49.69702	0.0000

AVAX Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	3721.288	AIC	=	-17.32999
FPE	=	2.05E-14	HQIC	=	-17.2172
Det(Sigma_ml)	=	1.78E-14	SBIC	=	-17.04446

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pAVAXMC	6	0.044077	0.0169	7.343971	0.1963
pAVAXV	6	0.406009	0.0534	24.02794	0.0002
pAVAXCS	6	0.003665	0.0266	11.63426	0.0402
pAVAXTVL	6	0.115995	0.1023	48.53482	0.0000
pBTCP	6	0.024067	0.0265	11.60067	0.0407

TRX Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	5537.161	AIC	=	-25.85522
FPE	=	4.06E-18	HQIC	=	-25.74243
Det(Sigma_ml)	=	3.53E-18	SBIC	=	-25.56969

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pTRXMC	6	0.01782	0.0786	36.34041	0.0000
pTRXV	6	0.341833	0.0339	14.96444	0.0105
pTRXCS	6	0.000982	0.1938	102.4336	0.0000
pTRXTVL	6	0.019916	0.0165	7.148901	0.2098
pBTCP	6	0.023471	0.0742	34.13365	0.0000

MATIC Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	4844.977	AIC	=	-22.60553
FPE	=	1.05E-16	HQIC	=	-22.49274
Det(Sigma_ml)	=	9.10E-17	SBIC	=	-22.32

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pMATICMC	6	0.035722	0.1307	64.03317	0.0000
pMATICV	6	0.408352	0.0270	11.83627	0.0371
pMATICCS	6	0.002352	0.1784	92.48709	0.0000
pMATICTVL	6	0.021494	0.0205	8.91991	0.1123
pBTCP	6	0.023340	0.0845	39.31143	0.0000

BNB Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	4785.081	AIC	=	-22.32433
FPE	=	1.39E-16	HQIC	=	-22.21154
Det(Sigma_ml)	=	1.21E-16	SBIC	=	-22.0388

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pBNBMC	6	0.023537	0.1755	90.69052	0.0000
pBNBV	6	0.635833	0.0447	19.9516	0.0013
pBNBCS	6	0.001907	0.1967	104.3152	0.0000
pBNBTVL	6	0.024313	0.0337	14.8404	0.0111
pBTCP	6	0.023865	0.0428	19.04781	0.0019

OP Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	3285.184	AIC	=	-15.28255
FPE	=	1.59E-13	HQIC	=	-15.16976
Det(Sigma_ml)	=	1.38E-13	SBIC	=	-14.99703

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pOPMC	6	0.066305	0.0487	21.78751	0.0006
pOPV	6	0.501677	0.0297	13.03116	0.0231
pOPCS	6	0.045490	0.0122	5.25582	0.3855
pOPTVL	6	0.021767	0.0151	6.526413	0.2583
pBTCP	6	0.023990	0.0327	14.41767	0.0132

SOL Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	4346.68	AIC	=	-20.26611
FPE	=	1.09E-15	HQIC	=	-20.15332
Det(Sigma_ml)	=	9.44E-16	SBIC	=	-19.98058

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pSOLMC	6	0.045103	0.0645	29.35421	0.0000
pSOLV	6	0.522687	0.0332	14.63449	0.0120
pSOLCS	6	0.002306	0.1280	62.52108	0.0000
pSOLTVL	6	0.040812	0.0256	11.17163	0.0481
pBTCP	6	0.023925	0.0380	16.82681	0.0048

FTM Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	4018.505	AIC	=	-18.72538
FPE	=	5.07E-15	HQIC	=	-18.61259
Det(Sigma_ml)	=	4.41E-15	SBIC	=	-18.43985

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pFTMMC	6	0.048477	0.0389	17.25193	0.004
pFTMV	6	0.408957	0.0884	41.30192	0.000
pFTMCS	6	0.002432	0.2179	118.6773	0.000
pFTMTVL	6	0.078840	0.0355	15.67061	0.008
pBTCP	6	0.024053	0.0277	12.13231	0.033

ARB Vector Autoregression

Sample: 2 thru 427			No. of Obs	=	426
Log likelihood	=	3414.064	AIC	=	-15.88763
FPE	=	8.66E-14	HQIC	=	-15.77484
Det(Sigma_ml)	=	7.53E-14	SBIC	=	-15.6021

Equation	Parms	RMSE	R-sq	chi2	P>chi2
pARBMC	6	0.056601	0.0502	22.52645	0.0004
pARBV	6	0.55814	0.0370	16.38006	0.0058
pARBCS	6	0.041269	0.0225	9.816163	0.0806
pARBTVL	6	0.021533	0.0190	8.267177	0.1421
pBTCP	6	0.023265	0.0904	42.31751	0.0000

Figure 8: VAR Model Results for Cryptocurrencies

ETH

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pETHMC						
pETHMC	-0.376	0.088	-4.280	0.000	-0.548	-0.204
pETHV	0.000	0.002	-0.130	0.898	-0.004	0.004
pETHCS	-1.304	0.594	-2.200	0.028	-2.468	-0.140
pETHTVL	0.610	0.080	7.590	0.000	0.452	0.768
pBTCP	-0.198	0.084	-2.370	0.018	-0.362	-0.034
_cons	0.002	0.001	1.810	0.070	0.000	0.005
pETHV						
pETHMC	-2.035	2.148	-0.950	0.343	-6.244	2.174
pETHV	-0.108	0.049	-2.230	0.026	-0.204	-0.013
pETHCS	-8.173	14.515	-0.560	0.573	-36.623	20.276
pETHTVL	1.410	1.965	0.720	0.473	-2.441	5.261
pBTCP	1.930	2.044	0.940	0.345	-2.077	5.937
_cons	0.125	0.031	4.060	0.000	0.065	0.186
pETHCS						
pETHMC	0.006	0.007	0.850	0.394	-0.007	0.019
pETHV	0.000	0.000	1.300	0.194	0.000	0.000
pETHCS	-0.338	0.045	-7.480	0.000	-0.426	-0.249
pETHTVL	-0.021	0.006	-3.510	0.000	-0.033	-0.009
pBTCP	0.014	0.006	2.230	0.026	0.002	0.027
_cons	0.000	0.000	-0.400	0.689	0.000	0.000
pETHTVL						
pETHMC	-0.186	0.083	-2.250	0.025	-0.348	-0.024
pETHV	0.001	0.002	0.340	0.733	-0.003	0.004
pETHCS	-1.188	0.559	-2.130	0.034	-2.284	-0.092
pETHTVL	0.210	0.076	2.770	0.006	0.061	0.358
pBTCP	-0.089	0.079	-1.130	0.260	-0.243	0.066
_cons	0.002	0.001	1.610	0.108	0.000	0.004
pBTCP						
pETHMC	-0.336	0.079	-4.250	0.000	-0.491	-0.181
pETHV	0.001	0.002	0.540	0.590	-0.003	0.004
pETHCS	-1.377	0.534	-2.580	0.010	-2.423	-0.331
pETHTVL	0.414	0.072	5.730	0.000	0.272	0.556
pBTCP	-0.082	0.075	-1.090	0.277	-0.229	0.066
_cons	0.002	0.001	2.130	0.033	0.000	0.005

TRX

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pTRXMC						
pTRXMC	0.006	0.053	0.110	0.916	-0.099	0.110
pTRXV	0.002	0.003	0.950	0.342	-0.003	0.007
pTRXCS	-1.150	0.790	-1.460	0.145	-2.698	0.397
pTRXTVL	0.241	0.055	4.400	0.000	0.133	0.348
pBTCP	-0.251	0.047	-5.380	0.000	-0.342	-0.159
_cons	0.001	0.001	1.600	0.109	0.000	0.003
pTRXV						
pTRXMC	-1.542	1.024	-1.510	0.132	-3.548	0.465
pTRXV	-0.155	0.048	-3.230	0.001	-0.249	-0.061
pTRXCS	-7.515	15.148	-0.500	0.620	-37.204	22.174
pTRXTVL	-0.765	1.048	-0.730	0.465	-2.819	1.288
pBTCP	1.074	0.893	1.200	0.229	-0.677	2.824
_cons	0.051	0.017	3.040	0.002	0.018	0.083
pTRXCS						
pTRXMC	0.001	0.003	0.250	0.801	-0.005	0.007
pTRXV	0.000	0.000	1.090	0.274	0.000	0.000
pTRXCS	-0.431	0.044	-9.900	0.000	-0.516	-0.346
pTRXTVL	-0.005	0.003	-1.640	0.101	-0.011	0.001
pBTCP	0.003	0.003	1.230	0.219	-0.002	0.008
_cons	0.000	0.000	-3.060	0.002	0.000	0.000
pTRXTVL						
pTRXMC	0.030	0.060	0.510	0.611	-0.087	0.147
pTRXV	0.000	0.003	0.070	0.947	-0.005	0.006
pTRXCS	0.861	0.883	0.980	0.329	-0.869	2.590
pTRXTVL	0.051	0.061	0.830	0.405	-0.069	0.171
pBTCP	-0.124	0.052	-2.390	0.017	-0.226	-0.022
_cons	0.002	0.001	1.570	0.117	0.000	0.003
pBTCP						
pTRXMC	-0.152	0.070	-2.160	0.031	-0.289	-0.014
pTRXV	0.000	0.003	0.050	0.957	-0.006	0.007
pTRXCS	-0.265	1.040	-0.260	0.799	-2.304	1.773
pTRXTVL	0.376	0.072	5.220	0.000	0.235	0.517
pBTCP	-0.236	0.061	-3.840	0.000	-0.356	-0.115
_cons	0.003	0.001	2.270	0.023	0.000	0.005

BNB

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pBNBMC						
pBNBMC	-0.024	0.056	-0.430	0.667	-0.133	0.085
pBNBV	0.001	0.002	0.450	0.653	-0.003	0.004
pBNBCS	0.470	0.543	0.870	0.387	-0.595	1.535
pBNBTVL	0.471	0.053	8.850	0.000	0.366	0.575
pBTCP	-0.337	0.059	-5.710	0.000	-0.453	-0.222
_cons	0.002	0.001	2.010	0.044	0.000	0.005
pBNBV						
pBNBMC	-1.440	1.507	-0.960	0.339	-4.394	1.514
pBNBV	-0.115	0.047	-2.430	0.015	-0.207	-0.022
pBNBCS	9.728	14.676	0.660	0.507	-19.037	38.494
pBNBTVL	2.709	1.437	1.880	0.059	-0.108	5.525
pBTCP	3.370	1.597	2.110	0.035	0.240	6.501
_cons	0.136	0.031	4.320	0.000	0.074	0.197
pBNBCS						
pBNBMC	0.009	0.005	2.050	0.041	0.000	0.018
pBNBV	0.000	0.000	0.770	0.440	0.000	0.000
pBNBCS	-0.402	0.044	-9.140	0.000	-0.489	-0.316
pBNBTVL	-0.011	0.004	-2.580	0.010	-0.020	-0.003
pBTCP	0.008	0.005	1.660	0.098	-0.001	0.017
_cons	0.000	0.000	-1.390	0.166	0.000	0.000
pBNBTVL						
pBNBMC	-0.158	0.058	-2.750	0.006	-0.271	-0.045
pBNBV	-0.002	0.002	-1.110	0.266	-0.006	0.002
pBNBCS	0.366	0.561	0.650	0.514	-0.734	1.466
pBNBTVL	-0.018	0.055	-0.330	0.740	-0.126	0.089
pBTCP	0.022	0.061	0.370	0.713	-0.097	0.142
_cons	0.001	0.001	0.710	0.479	-0.002	0.003
pBTCP						
pBNBMC	-0.140	0.057	-2.480	0.013	-0.251	-0.029
pBNBV	0.003	0.002	1.520	0.130	-0.001	0.006
pBNBCS	-0.089	0.551	-0.160	0.872	-1.168	0.991
pBNBTVL	0.169	0.054	3.130	0.002	0.063	0.275
pBTCP	-0.092	0.060	-1.530	0.126	-0.209	0.026
_cons	0.002	0.001	2.030	0.043	0.000	0.005

SOL

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pSOLMC						
pSOLMC	-0.001	0.070	-0.010	0.992	-0.138	0.136
pSOLV	0.007	0.004	1.550	0.122	-0.002	0.015
pSOLCS	-2.114	0.895	-2.360	0.018	-3.868	-0.359
pSOLTVL	0.225	0.064	3.490	0.000	0.099	0.351
pBTCP	-0.381	0.116	-3.280	0.001	-0.609	-0.153
_cons	0.006	0.002	2.630	0.009	0.001	0.010
pSOLV						
pSOLMC	-0.613	0.809	-0.760	0.449	-2.199	0.973
pSOLV	-0.095	0.049	-1.950	0.051	-0.191	0.000
pSOLCS	-2.255	10.375	-0.220	0.828	-22.589	18.079
pSOLTVL	-0.516	0.746	-0.690	0.489	-1.978	0.946
pBTCP	4.061	1.347	3.010	0.003	1.420	6.701
_cons	0.102	0.026	3.910	0.000	0.051	0.153
pSOLCS						
pSOLMC	0.001	0.004	0.220	0.828	-0.006	0.008
pSOLV	0.000	0.000	0.220	0.826	0.000	0.000
pSOLCS	-0.330	0.046	-7.220	0.000	-0.420	-0.241
pSOLTVL	-0.005	0.003	-1.420	0.155	-0.011	0.002
pBTCP	0.012	0.006	2.060	0.040	0.001	0.024
_cons	0.001	0.000	4.720	0.000	0.000	0.001
pSOLTVL						
pSOLMC	0.033	0.063	0.520	0.606	-0.091	0.156
pSOLV	0.005	0.004	1.270	0.204	-0.003	0.012
pSOLCS	-1.042	0.810	-1.290	0.198	-2.630	0.546
pSOLTVL	-0.108	0.058	-1.860	0.063	-0.222	0.006
pBTCP	-0.158	0.105	-1.500	0.133	-0.364	0.048
_cons	0.008	0.002	3.830	0.000	0.004	0.012
pBTCP						
pSOLMC	-0.093	0.037	-2.500	0.012	-0.165	-0.020
pSOLV	-0.001	0.002	-0.430	0.669	-0.005	0.003
pSOLCS	-0.417	0.475	-0.880	0.380	-1.348	0.514
pSOLTVL	0.106	0.034	3.090	0.002	0.039	0.173
pBTCP	-0.053	0.062	-0.860	0.390	-0.174	0.068
_cons	0.003	0.001	2.170	0.030	0.000	0.005

ARB

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pARBMC						
pARBMC	-0.177	0.082	-2.170	0.030	-0.337	-0.017
pARBV	0.003	0.005	0.550	0.580	-0.007	0.013
pARBCS	0.236	0.105	2.260	0.024	0.031	0.441
pARBTVL	0.843	0.179	4.700	0.000	0.491	1.195
pBTCP	-0.332	0.146	-2.270	0.023	-0.619	-0.045
_cons	0.003	0.003	1.010	0.310	-0.003	0.008
pARBV						
pARBMC	-1.089	0.805	-1.350	0.176	-2.667	0.489
pARBV	-0.115	0.050	-2.300	0.021	-0.214	-0.017
pARBCS	1.712	1.031	1.660	0.097	-0.310	3.733
pARBTVL	2.859	1.769	1.620	0.106	-0.609	6.326
pBTCP	1.867	1.444	1.290	0.196	-0.963	4.697
_cons	0.103	0.028	3.760	0.000	0.049	0.157
pARBCS						
pARBMC	-0.089	0.060	-1.490	0.136	-0.206	0.028
pARBV	-0.001	0.004	-0.210	0.831	-0.008	0.006
pARBCS	0.075	0.076	0.980	0.325	-0.074	0.225
pARBTVL	-0.059	0.131	-0.450	0.650	-0.316	0.197
pBTCP	0.313	0.107	2.930	0.003	0.104	0.523
_cons	0.002	0.002	0.950	0.341	-0.002	0.006
pARBTVL						
pARBMC	0.035	0.031	1.140	0.255	-0.026	0.096
pARBV	0.000	0.002	-0.210	0.835	-0.004	0.003
pARBCS	-0.019	0.040	-0.470	0.639	-0.097	0.059
pARBTVL	0.089	0.068	1.300	0.193	-0.045	0.223
pBTCP	-0.155	0.056	-2.780	0.005	-0.264	-0.046
_cons	0.001	0.001	0.810	0.415	-0.001	0.003
pBTCP						
pARBMC	-0.049	0.034	-1.470	0.141	-0.115	0.016
pARBV	0.002	0.002	1.180	0.239	-0.002	0.007
pARBCS	-0.020	0.043	-0.450	0.650	-0.104	0.065
pARBTVL	0.358	0.074	4.860	0.000	0.214	0.503
pBTCP	-0.248	0.060	-4.130	0.000	-0.366	-0.130
_cons	0.003	0.001	2.340	0.019	0.000	0.005

AVAX

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pAVAXMC						
pAVAXMC	0.117	0.062	1.890	0.058	-0.004	0.238
pAVAXV	0.002	0.005	0.300	0.768	-0.009	0.012
pAVAXCS	-0.621	0.580	-1.070	0.284	-1.757	0.515
pAVAXTVL	0.000	0.018	-0.020	0.981	-0.035	0.034
pBTCP	-0.279	0.112	-2.500	0.012	-0.499	-0.060
_cons	0.004	0.002	1.620	0.105	-0.001	0.008
pAVAXV						
pAVAXMC	0.198	0.570	0.350	0.729	-0.919	1.314
pAVAXV	-0.171	0.048	-3.590	0.000	-0.264	-0.078
pAVAXCS	-3.175	5.339	-0.590	0.552	-13.639	7.290
pAVAXTVL	-0.061	0.162	-0.370	0.708	-0.378	0.256
pBTCP	2.482	1.030	2.410	0.016	0.463	4.501
_cons	0.076	0.020	3.770	0.000	0.036	0.115
pAVAXCS						
pAVAXMC	-0.004	0.005	-0.700	0.485	-0.014	0.006
pAVAXV	0.000	0.000	-0.270	0.787	-0.001	0.001
pAVAXCS	-0.151	0.048	-3.130	0.002	-0.245	-0.057
pAVAXTVL	-0.001	0.001	-0.430	0.670	-0.003	0.002
pBTCP	0.008	0.009	0.880	0.378	-0.010	0.026
_cons	0.001	0.000	2.840	0.004	0.000	0.001
pAVAXTVL						
pAVAXMC	0.448	0.163	2.750	0.006	0.129	0.767
pAVAXV	-0.015	0.014	-1.130	0.257	-0.042	0.011
pAVAXCS	0.402	1.525	0.260	0.792	-2.588	3.391
pAVAXTVL	-0.300	0.046	-6.480	0.000	-0.390	-0.209
pBTCP	-0.244	0.294	-0.830	0.406	-0.821	0.332
_cons	0.005	0.006	0.930	0.352	-0.006	0.017
pBTCP						
pAVAXMC	-0.067	0.034	-1.980	0.048	-0.133	-0.001
pAVAXV	-0.003	0.003	-1.220	0.222	-0.009	0.002
pAVAXCS	-0.159	0.316	-0.500	0.615	-0.780	0.461
pAVAXTVL	0.007	0.010	0.680	0.497	-0.012	0.025
pBTCP	-0.030	0.061	-0.480	0.628	-0.149	0.090
_cons	0.003	0.001	2.450	0.014	0.001	0.005

MATIC

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pMATICMC						
pMATICMC	-0.147	0.064	-2.290	0.022	-0.273	-0.021
pMATICV	0.000	0.004	-0.080	0.936	-0.009	0.008
pMATICCS	-0.707	0.668	-1.060	0.290	-2.017	0.603
pMATICTVL	0.763	0.111	6.890	0.000	0.546	0.980
pBTCP	-0.517	0.095	-5.420	0.000	-0.704	-0.330
_cons	0.001	0.002	0.550	0.579	-0.002	0.004
pMATICV						
pMATICMC	-0.473	0.735	-0.640	0.520	-1.913	0.967
pMATICV	-0.131	0.048	-2.730	0.006	-0.225	-0.037
pMATICCS	-9.858	7.641	-1.290	0.197	-24.834	5.118
pMATICTVL	-0.626	1.266	-0.490	0.621	-3.107	1.856
pBTCP	1.825	1.091	1.670	0.094	-0.314	3.963
_cons	0.070	0.020	3.470	0.001	0.030	0.109
pMATICCS						
pMATICMC	-0.006	0.004	-1.510	0.132	-0.015	0.002
pMATICV	0.000	0.000	1.110	0.269	0.000	0.001
pMATICCS	-0.413	0.044	-9.380	0.000	-0.499	-0.327
pMATICTVL	-0.004	0.007	-0.560	0.576	-0.018	0.010
pBTCP	0.013	0.006	2.070	0.038	0.001	0.025
_cons	0.000	0.000	0.210	0.831	0.000	0.000
pMATICTVL						
pMATICMC	0.011	0.039	0.280	0.776	-0.065	0.087
pMATICV	0.002	0.003	0.680	0.493	-0.003	0.007
pMATICCS	-0.422	0.402	-1.050	0.294	-1.211	0.366
pMATICTVL	0.092	0.067	1.380	0.168	-0.039	0.222
pBTCP	-0.146	0.057	-2.550	0.011	-0.259	-0.034
_cons	0.000	0.001	0.140	0.886	-0.002	0.002
pBTCP						
pMATICMC	-0.113	0.042	-2.700	0.007	-0.196	-0.031
pMATICV	0.002	0.003	0.630	0.526	-0.004	0.007
pMATICCS	-0.570	0.437	-1.300	0.192	-1.425	0.286
pMATICTVL	0.407	0.072	5.630	0.000	0.265	0.549
pBTCP	-0.206	0.062	-3.300	0.001	-0.328	-0.083
_cons	0.003	0.001	2.400	0.016	0.001	0.005

OP

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pOPMC						
pOPMC	-0.169	0.079	-2.140	0.033	-0.324	-0.014
pOPV	0.009	0.007	1.240	0.214	-0.005	0.023
pOPCS	0.164	0.104	1.580	0.115	-0.040	0.367
pOPTVL	0.833	0.191	4.370	0.000	0.459	1.207
pBTCP	-0.473	0.163	-2.910	0.004	-0.793	-0.154
_cons	0.006	0.003	1.690	0.090	-0.001	0.012
pOPV						
pOPMC	0.112	0.598	0.190	0.851	-1.060	1.285
pOPV	-0.095	0.053	-1.780	0.075	-0.200	0.010
pOPCS	-0.736	0.785	-0.940	0.349	-2.275	0.803
pOPTVL	2.619	1.444	1.810	0.070	-0.211	5.449
pBTCP	0.264	1.233	0.210	0.830	-2.152	2.680
_cons	0.098	0.025	3.940	0.000	0.049	0.146
pOPCS						
pOPMC	-0.113	0.054	-2.080	0.037	-0.219	-0.007
pOPV	0.008	0.005	1.750	0.080	-0.001	0.018
pOPCS	0.100	0.071	1.410	0.160	-0.039	0.240
pOPTVL	0.078	0.131	0.600	0.550	-0.178	0.335
pBTCP	0.042	0.112	0.380	0.705	-0.177	0.261
_cons	0.003	0.002	1.310	0.190	-0.001	0.007
pOPTVL						
pOPMC	0.038	0.026	1.480	0.139	-0.013	0.089
pOPV	0.001	0.002	0.490	0.625	-0.003	0.006
pOPCS	-0.033	0.034	-0.960	0.335	-0.100	0.034
pOPTVL	0.009	0.063	0.150	0.882	-0.113	0.132
pBTCP	-0.100	0.053	-1.870	0.061	-0.205	0.005
_cons	0.000	0.001	0.150	0.879	-0.002	0.002
pBTCP						
pOPMC	-0.002	0.029	-0.080	0.936	-0.058	0.054
pOPV	0.004	0.003	1.460	0.143	-0.001	0.009
pOPCS	-0.018	0.038	-0.480	0.633	-0.092	0.056
pOPTVL	0.169	0.069	2.450	0.014	0.034	0.305
pBTCP	-0.186	0.059	-3.160	0.002	-0.302	-0.071
_cons	0.003	0.001	2.130	0.033	0.000	0.005

FTM

L1	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
pFTMMC						
pFTMMC	0.006	0.061	0.110	0.915	-0.113	0.126
pFTMV	-0.002	0.006	-0.340	0.735	-0.013	0.009
pFTMCS	-0.962	0.857	-1.120	0.262	-2.643	0.718
pFTMTVL	0.115	0.033	3.470	0.001	0.050	0.181
pBTCP	-0.232	0.117	-1.990	0.047	-0.461	-0.003
_cons	0.003	0.002	1.230	0.217	-0.002	0.008
pFTMV						
pFTMMC	0.009	0.514	0.020	0.986	-0.999	1.017
pFTMV	-0.162	0.047	-3.420	0.001	-0.255	-0.069
pFTMCS	-24.030	7.233	-3.320	0.001	-38.205	-9.854
pFTMTVL	0.734	0.280	2.620	0.009	0.185	1.284
pBTCP	1.763	0.984	1.790	0.073	-0.166	3.692
_cons	0.075	0.020	3.760	0.000	0.036	0.115
pFTMCS						
pFTMMC	-0.002	0.003	-0.520	0.603	-0.008	0.004
pFTMV	0.001	0.000	2.870	0.004	0.000	0.001
pFTMCS	-0.430	0.043	-9.990	0.000	-0.514	-0.345
pFTMTVL	-0.001	0.002	-0.310	0.760	-0.004	0.003
pBTCP	0.017	0.006	2.830	0.005	0.005	0.028
_cons	0.000	0.000	-0.510	0.613	0.000	0.000
pFTMTVL						
pFTMMC	0.056	0.099	0.560	0.574	-0.139	0.250
pFTMV	-0.006	0.009	-0.690	0.490	-0.024	0.012
pFTMCS	1.532	1.394	1.100	0.272	-1.201	4.265
pFTMTVL	-0.157	0.054	-2.910	0.004	-0.263	-0.051
pBTCP	-0.277	0.190	-1.460	0.144	-0.649	0.095
_cons	0.003	0.004	0.850	0.393	-0.004	0.011
pBTCP						
pFTMMC	-0.008	0.030	-0.250	0.802	-0.067	0.052
pFTMV	0.004	0.003	1.430	0.153	-0.001	0.009
pFTMCS	-0.292	0.425	-0.690	0.493	-1.125	0.542
pFTMTVL	0.035	0.016	2.140	0.032	0.003	0.068
pBTCP	-0.124	0.058	-2.140	0.032	-0.237	-0.010
_cons	0.002	0.001	2.000	0.046	0.000	0.005

Figure 9: VAR Model Lag Results for All 5 Variables

data points that are closer to the regression with less errors. Except for trading volume which logically has a larger variation due to the volatility of crypto, most of our variables exhibit a low RMSE reducing the likelihood for errors. R^2 is a percentage value that measures the probability that the VAR model reproduces the observed outcomes. Although our variables exhibit low R^2, this should not be alarming as crypto markets are less predictable that traditional assets (Bianchi *et al.*, 2022). As a result, there would be a lower percentage chance that the model is able to replicate the observed outcomes with standard age-old statistical tools. The P>chi² highlights any statistically significant (p-values < 0.05) variables that represent the VAR model well. In this instance, the null hypothesis is not rejected for the following variables: ETHV, AVAXMC, TRXTVL, MATICTVL, OPCS, OPTVL, ARBCS, ARBTVL. Trading volume might not affect the remaining ETHV valuation models which could be due to their position as the most established and matured altcoin ecosystem. ARB and OP are relatively new cryptocurrencies, whereby their assets locked within their ecosystem and inflationary mechanisms have yet to stabilize amongst investor behavior. There might be a lack of investor interest in AVAXMC. TRXTVL and MATICTVL suggest that their ecosystems are either resilient to external market factors, whether it is due to confidence or a lack there of would require more investigation. These findings are displayed in Figure 8.

Based on the *P*>*z* results across all cryptocurrencies, the performance metric variables are represented well by the selected lag order of 1, providing statistically significant results for ~50%. These observations are highlighted in Figure 9.

6. Description and Analysis of IRF Results

6.1. Impulse Response Functions (IRFs)

Impulse Response Functions (IRFs) are vital for capturing interdependencies and temporal dynamics by charting a time path to illustrate the impact of shocks to response variables among these cryptocurrencies. IRFs depicts what happens when one standard deviation shock is applied via an impulse variable to a response variable over a set time period (Polyzos, 2023). The responses are displayed within a 95% confidence interval range and the IRFs are orthogonalized to show the variability surrounding these estimations across an 8-step horizon. The results shown in Figures 10 to 14 reveal several patterns, trends, and outliers amongst the variables across the cryptocurrencies.

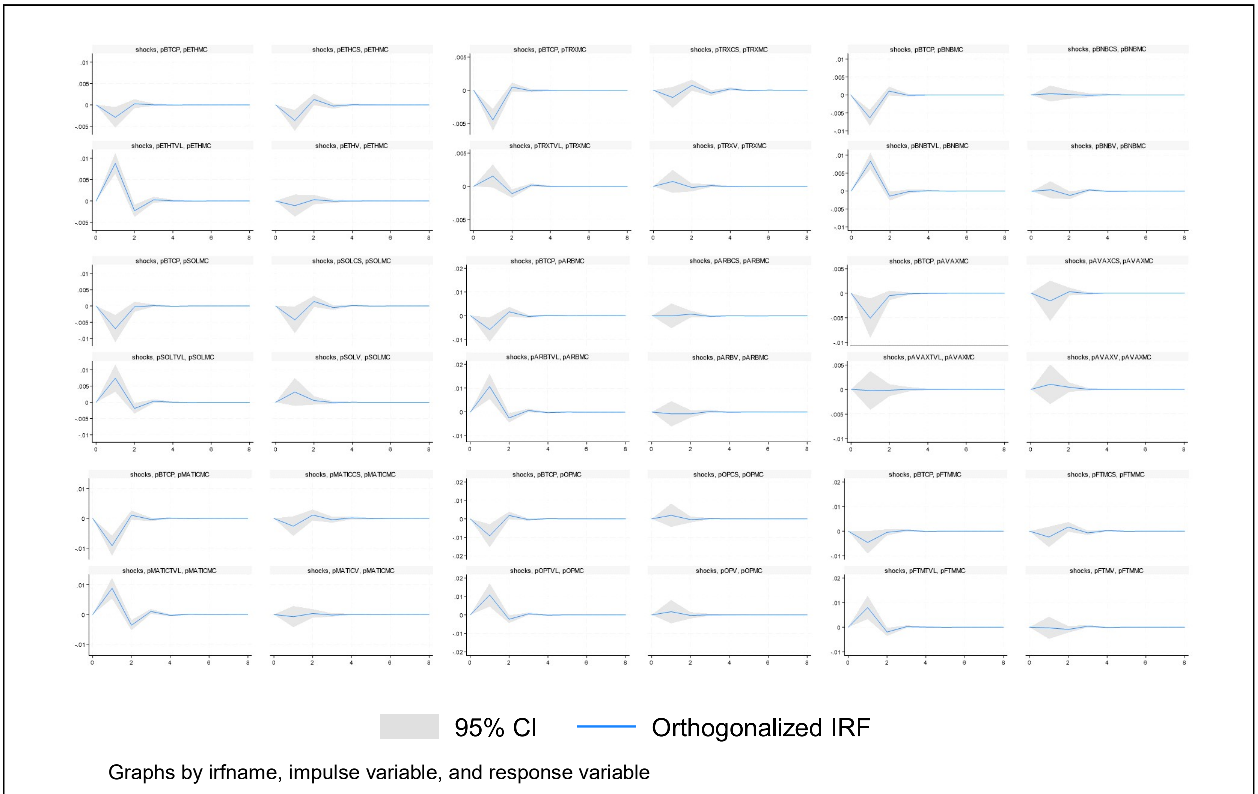

Figure 10: Impulse Response Function Results (Market Capitalization Resposes to Shocks)

6.1.1. Market Capitalization (MC) Responses to Shocks

Bitcoin price (BTCP) shocks generally provoke a negative response in all crypto chain market capitalizations. This phenomenon could be attributed towards Bitcoin dominance (Coingecko). Being the largest and most established cryptocurrency, Bitcoin often dictates the entire crypto market sentiment. When the price of Bitcoin rises, investors may reallocate their investments into Bitcoin which is typically perceived as the safer asset, thus reducing the market capitalization of altcoins temporarily. Furthermore, in most exchanges, the most popular non-fiat trading pair for all cryptocurrencies is "/BTC" which means that most cryptocurrencies are pegged against Bitcoin. This magnifies the occurrence as the Bitcoin price increase causes sell orders of BTC trading pairs to execute. These actions are carried out by automated trading systems and algorithms which tracks the performance of Bitcoin, triggering altcoin sell-offs and or reallocations into Bitcoin. Eventually, altcoins tend to stabilize which reflects a decoupling or recovery from drastic changes in BTC prices. Circulating supply (CS) shocks causes ETH, TRX, SOL, AVAX, MATIC, FTM to show a negative response and a subsequent positive bounce before stabilizing. This suggests that inflationary pressures can dilute the value of ecosystems, which causes market capitalizations to drop initially. However, if there are perceived growth or utility within these matured ecosystems, such as an increase in token usage for transitionary purposes, then market capitalizations could rebound positively. The lack of response from BNB, ARB and OP towards CS shocks suggests that there are strong inflationary mechanisms in place. For example, Binance adopts a strategy of burning tokens quarterly in which BNB coins are sent to a wallet address that can only receive coins, without the ability to send any out. This essentially destroys the additional surplus and maintains the value of the remaining BNB coins, countering the effects of inflationary pressures. Meanwhile, it is possible that investors might not fully grasp the technological inflationary mechanisms of ARB and OP as they are relatively newer cryptocurrencies. Their fundamentals and potential for growth in the long term could still be under review which could be causing the inappropriate market response currently observed whereby the investment capital inflow outweigh inflationary impacts in newer cryptocurrencies. Most crypto market capitalizations show an initial positive response to shocks from Total Value Locked (TVL), followed by a negative bounce before stabilizing. A higher TVL reflects more confidence and usage of DeFi applications within these ecosystems, which attracts more investments into these cryptocurrencies, boosting their respective market capitalizations. The lack of response from AVAX's MC to TVL shocks could be due to external qualitative factors such as previous scandals, causing a significant destruction of interest in the chain. Trading Volume (V) induces minor fluctuations in market capitalizations before stabilizing around zero indicating that trading volume only causes temporary volatility and do not have lasting long-term impacts on market capitalizations. Across all variable shocks, most cryptocurrencies display a narrow or moderate confidence interval. Only AVAX displays a wide confidence interval suggesting more uncertainty and variability in the responses. These results can be observed from Figure 10.

6.1.2. Trading Volume (V) Responses to Shocks

Bitcoin price (BTCP) shocks on trading volume show a positive response on all cryptocurrencies except for Optimism (OP), which does not warrant much significant response. This suggests that BTCP movements are likened towards investor sentiments, driving trading volumes across the board. Whereas OP's trading volume could be skewed towards a niche market or specific investor base. Most cryptocurrencies exhibit minor fluctuations from Circulating Supply (CS) shocks. The study notes that AVAX, MATIC, OP, FTM display an initial negative response followed by a positive spike before stabilizing. This observation suggests that while inflation might bring about initial token dilution concerns, inflationary pressures are generally small and stabilize quickly within these ecosystem chains. This could also be due to traders rebalancing their portfolios after new supply considerations. For market capitalization (MC) shocks on volume, all cryptocurrencies produce an instantaneous unseen positive spike before a negative decline towards stabilization at zero. This pattern suggests that while market capitalizations shocks have an immediate positive influence over trading volumes, these effects do not last as markets readjusts and stabilizes as traders react quickly. Shocks caused by Total Value Locked (TVL) causes a positive response in BNB, ARB, OP and FTM. This implies that a rise in TVL shows an increased engagement in DeFi apps reflecting more capital being locked within the ecosystem. This results in more investor interest who participate in trading activities boosting trading volumes. On the contrary, the remaining cryptocurrencies trading volumes could have significant influence from other factors which explains the limited responses towards TVL shocks. While most cryptocurrencies exhibits either a moderate or narrow confidence interval, BNB, AVAX and MATIC displays a wide confidence interval, indicating higher uncertainty and variability in their trading volumes. These results can be observed from Figure 11.

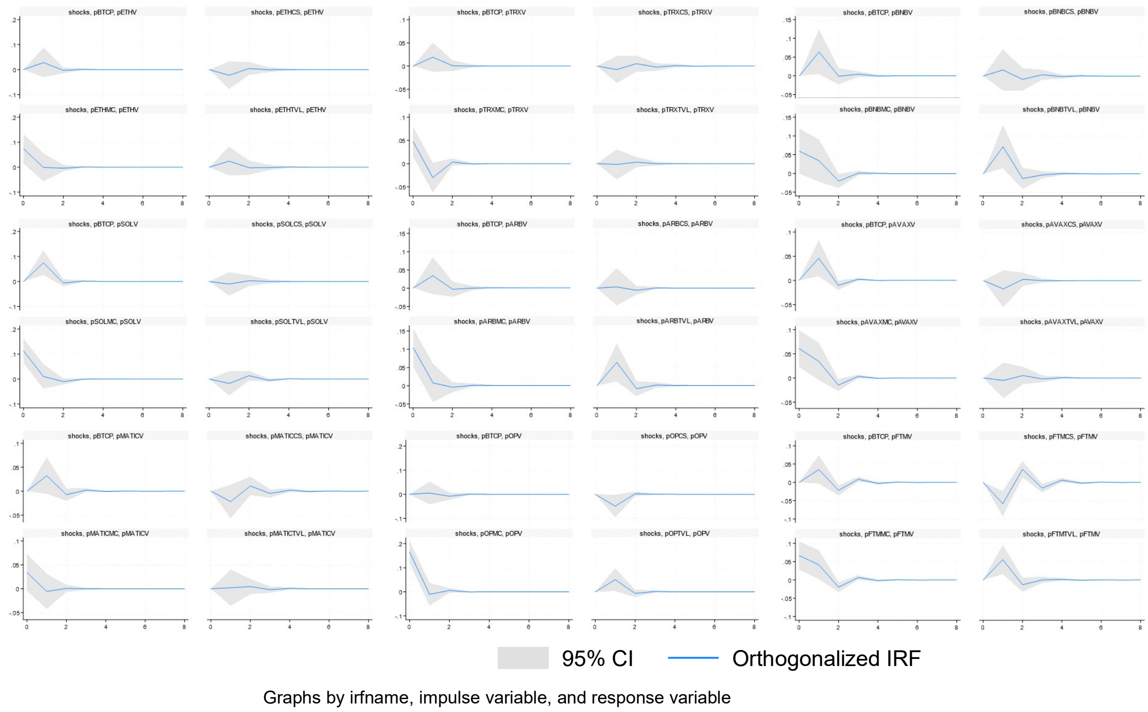

Figure 11: Impulse Response Function Results (Trading Volume Resposes to Shocks)

6.1.3. Circulating Supply (CS) Responses to Shocks

Degrees of circulating supply responses are very small being ranging around 0.0005 for most cryptocurrencies, suggesting that CS is resistant to shocks from external factors. Only the newer cryptocurrencies ARB and OP

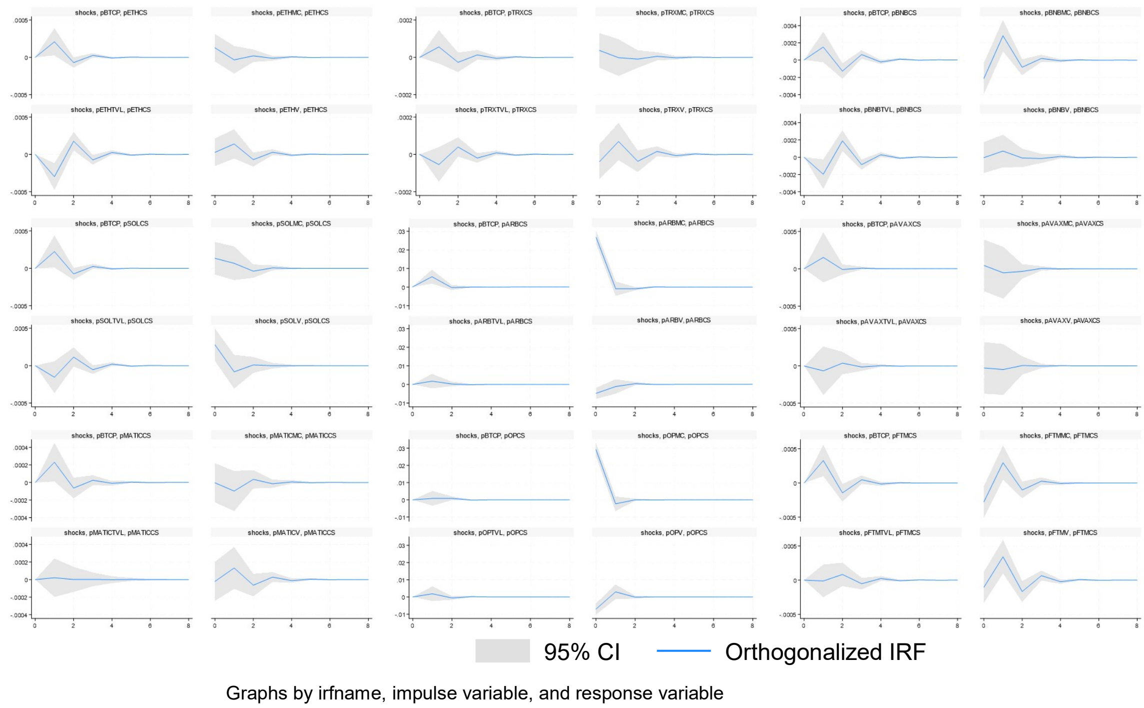

Figure 12: Impulse Response Function Results (Circulating Supply Resposes to Shocks)

have degrees below 0.3. As the magnitude of responses are relatively small, BTCP does not have much influence over inflationary pressures in altcoin ecosystems except for ARB which shows a positive response (0.005). This suggests that circulating supply changes are more likely driven by internal inflationary mechanisms or protocols. Regarding market capitalization (MC) shocks, ARB and OP are sensitive to market capitalization (MC) shocks as they display notable sharp declines from an unseen positive spike (0.3). This suggests that CS in newer cryptocurrencies is driven by external investment factors rather than internal protocol mechanisms. Total Value Locked (TVL) shocks do not warrant any significant responses among these ecosystem chains suggesting that circulating supplies are not tied closely to the amount of locked capital within DeFi apps. Trading Volume (V) shocks on circulating supply induces ARB, OP to have an initial unseen negative spike (0.005) and a subsequent positive increase towards zero. This suggests that shocks from trading volumes causes a reduction in circulating supply initially for newer cryptocurrencies. Whereas for matured ecosystems, trading activity does not have much influence over circulating supply. As magnitudes of these cryptocurrencies are small, most of these responses are relatively consistent and predictable. These results can be observed from Figure 12.

6.1.4. Total Value Locked (TVL) Responses to Shocks

Based on the results of the IRFs, the impact of Trading Volume shocks is minimal but trigger varied responses for different chains. Bitcoin price (pBTCP) shocks on total value locked warrants a negative response in TRX, AVAX, MATIC, OP, FTM, albeit of a lower magnitude in ETH, SOL, and ARB. Interestingly, this suggests that BTCP increases results in withdrawals from DeFi apps within these ecosystems. Investors could have more confidence in ETH, SOL, and ARB, resulting in DeFi ecosystems that are more resilient towards external BTCP shocks. Similarly, BNB is also resistant to BTCP shocks as they do not possess significant responses in this regard. Circulating supply (CS) shocks on TVL cause an initial unseen negative spike in ARB, OP and AVAX, whereby ARB and OP has a steep recovery towards stabilization as compared to a slower recovery in AVAX. This implies that inflation does indeed erode value among these DeFi ecosystems. Minor fluctuation responses are observed in ETH, TRX, BNB, SOL, FTM which suggests that TVL in matured ecosystems are more resilient to inflationary shocks. TVL in TRX, BNB, and FTM display minor positive responses from CS shocks, suggesting that increased liquidity may improve economic activities. On the other hand, ETH, and SOL display minor negative responses instead, suggesting that an increased circulating supply dilutes the valuations of the

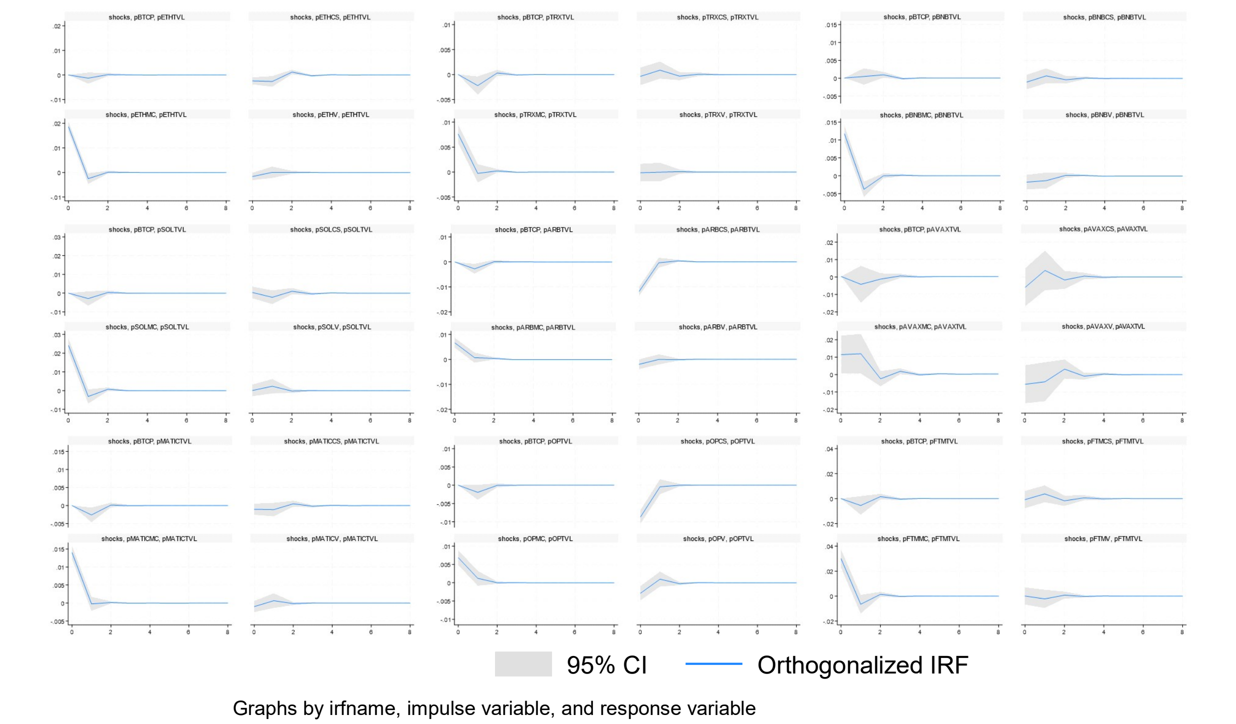

Figure 13: Impulse Response Function Results (Total Value Locked Resposes to Shocks)

tokens before stabilizations. Market capitalization (MC) shocks on TVL prompt a sharp instantaneous unseen positive spike, followed by a sharp negative decline towards zero before stabilizing in all cryptocurrencies. This implies that the increased market capitalizations could attract individuals to invest in DeFi apps within these crypto ecosystems, though the effect is not lasting in the long term as they stabilize by step 2. Only AVAX displays a delayed corrective response to the initial unseen positive spike, stabilizing by step 3. Perhaps, delayed reactions from investors due to the lack of active interest in the chain. In trading volume (V) shocks, positive responses of a small magnitude are observed in ARB, AVAX, OP. This implies that an increase in trading activity could slightly influence TVL positively. One possible theory is that an increased investor interest through higher trading volumes would serve as a signal for strength in the network and ecosystems for newer cryptocurrencies. Unfortunately, this might not be the case for matured ecosystems as not much significant responses are recorded in ETH, TRX, BNB, SOL, FTM. The narrow confidence intervals found in most of the cryptocurrencies indicate precise estimates, while the wide confidence interval in AVAX suggests a larger variability in the responses. These results can be observed from Figure 13.

6.1.5. Bitcoin Price (BTCP) Responses to Shocks

Variable shocks to Bitcoin price tend to be very responsive. Altcoin Circulating Supply (CS) shocks on Bitcoin price causes ARB, OP to have an initial unseen negative spike before a positive correction. ETH and MATIC also displays a negative response before stabilization. TRX, BNB, SOL, AVAX, FTM do not show any significant response. These results suggest that circulating supply increases in altcoins tend causes dilutions, which may result in lesser investment competition for BTC, causes the price to rise. These effects tend to have a faster correction in newer cryptocurrencies than matured ones, possibly due to the lack of understanding of their inflationary mechanisms. Nevertheless, these effects could be offset by CS changes in other altcoins as BTC price movements are largely unaffected. Regarding altcoin Market Capitalization (MC) shocks on Bitcoin price, an instantaneous initial unseen positive spike occurs followed by a negative decline towards zero is observed for all cryptocurrencies. This suggests that the increased investment in altcoins reflected by market capitalization growth is quickly reallocated into BTC. Subsequently, portfolios could rebalance overtime as investors chase higher returns in altcoins resulting in the stabilization pattern of BTCP. For total value locked (TVL) shocks, a positive response is found in ETH, SOL, FTM. In addition, TRX, BNB, ARB, MATIC, OP displayed an initial unseen positive spike before their corrective decline towards zero. These results suggest

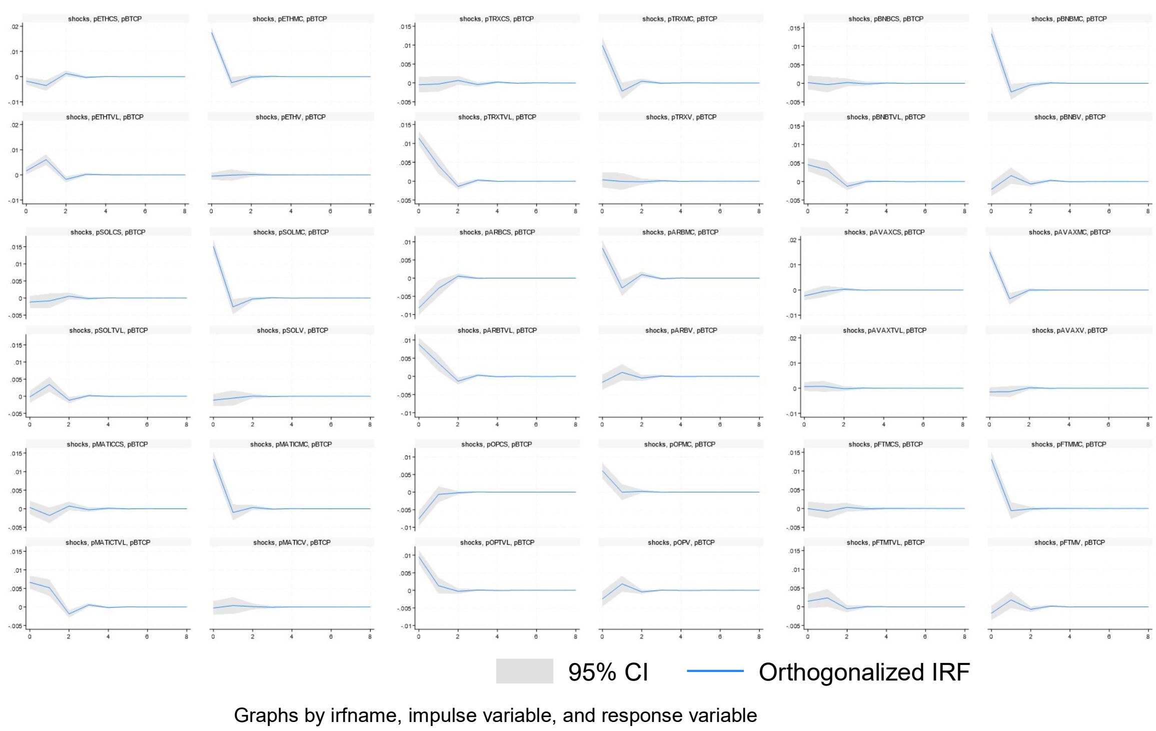

Figure 14: Impulse Response Function Results (Bitcoin Price Resposes to Shocks)

that increases in TVL within altcoin DeFi ecosystems have a positive influence over the price of BTC. Perhaps an improving growth and health of ecosystem chains reflected by the TVL could serve as a proxy for market confidence, which results in broader investments into the crypto markets which may trickle down into BTC. Unfortunately, this might not be foolproof as there are cryptocurrencies such as AVAX that does not exhibit a significant response in this matter. For trading volume (V) shocks, BNB, ARB, OP, FTM showcase a positive response before stabilizing. This suggests that trading volume increases for these cryptocurrencies may boost the price of BTC initially. Unfortunately, this is not consistent for all cryptocurrencies as minimal responses were seen from ETH, TRX SOL, AVAX, MATIC. Hence, this shows that BTC price is relatively stable and could be resistant towards trading volatility in altcoins. A narrow confidence interval observed for all altcoin variable shocks on Bitcoin price suggesting better precision in these predictive results. This also implies that BTC price movements are relatively stable with lower variability from external altcoin valuation shocks. These results can be observed from Figure 14.

7. Possible Explanations and Links to the Real World

The impact of different variable shocks on the cryptocurrency market is comprehensively understood through the use of Impulse Response Functions (IRFs). In this section, the overall results are discussed and interlinks with previous studies. These findings demonstrate established relationships between key variables and the development of various cryptocurrency ecosystems, including market capitalization, trading volume, circulating supply, Total Value Locked (TVL), trading volume, and Bitcoin price. Instead of suggesting that these distinct sole components are responsible for market fluctuations, our study emphasizes the complex relationships among these variables. Identifying how certain variables respond to different shocks can provide a better understanding for investment decisions and strategic planning. These insights are invaluable for analysts and investors as they offer a comprehensive framework for understanding these relationships, which may help in forecasting future shifts in the market and formulate better investment strategies. Ultimately, the study highlights the intricate interactions that these factors have with investor behavior, which together influence market dynamics.

7.1. Bitcoin Influence

These findings reveal that Bitcoin continues to have a strong influence over the entire cryptocurrency markets, including these ecosystem chains investigated. The valuation metrics of ecosystem chains such as market capitalization, trading volume, total value locked tend to fluctuate in the short term as investors and trading algorithms react to Bitcoin price changes. This often results in Bitcoin setting trends and dictating price movements of the cryptocurrency markets. In particular, Bitcoin declines might trigger market sell-offs due to widespread fear, uncertainty and doubt (Gandal *et al.*, 2018). This market influence is present in various aspects such as the initial negative responses of all ecosystem chains market capitalization to Bitcoin price shocks which highlights its role in establishing the tone of the market (Chu *et al.*, 2023). Moreover, trading volumes respond positively to Bitcoin price shocks, reinforcing its position as the market leader which drives up trading activity as investors seek to capitalize on opportunistic price movements or rebalance portfolios (Makridis *et al.*, 2023). In addition, the negative responses of TVL to Bitcoin price shocks, particularly in TRX, AVAX, MATIC, OP, and FTM, illustrates how a rise in Bitcoin's price can instigate a loss of confidence in some altcoins, triggering withdrawals from these DeFi ecosystems as investors seek alternative investments (Chiu *et al.*, 2022). The positive spikes in the price of Bitcoin following altcoin market capitalization shocks display market sentiment and investor behavior. Overtime, investors might seek to diversify their portfolios, redistributing their funds from Bitcoin into other cryptocurrencies, leading to a decline in the price of Bitcoin (Farooq *et al.*, 2022). This showcases the interconnectedness of the cryptocurrency markets where movements in one cryptocurrency can lead to large reallocations which affects other cryptocurrencies (Maouchi *et al.*, 2022). Ultimately, the study reveals the interconnectedness between these ecosystem chains and the price of Bitcoin, concluding that these ecosystem chains have yet to break away from Bitcoin dominance and gain independence.

7.2. Circulating Supply and Inflationary Dynamics

Inflation is the form of circulating supply increases causes tokens to dilute, causing market capitalizations to fall due to devaluation (Metelski and Sobieraj, 2022). The study finds that this is common among matured ecosystem chains which are susceptible towards inflationary pressures. On the other hand, there could be a lack of understanding and analysis of newer cryptocurrencies which results in a less than appropriate response towards inflation. The study also finds that although inflation dilutes and devalues the existing cryptocurrencies in circulation, certain mechanisms such as BNB's token burn can effectively counteract these effects. Additionally, if the market views perceive the increase in supply to be beneficial, for instance, positive developments in the form of enhanced utility or network growth, investors may regain confidence resulting in market capitalizations and trading volumes rebounding (Chiu *et al.*, 2022; Chu *et al.*, 2023). Interestingly, ARB and OP volume shocks have an immediate response towards circulating supply which could be because they are relatively newer cryptocurrencies and are highly susceptible to trading. Nevertheless, these findings suggest that CS is generally less influential as a valuation metric as compared to other variables like BTCP or TVL.

7.3. Total Value Locked as an Indicator

As Total Value Locked (TVL) remains the one of the most influential variables that consistently produces significant results, TVL could serve as a vital indicator that reflects the health and robustness of an ecosystem chain. TVL reflects the amount of capital locked within DeFi applications in an ecosystem chain whereby a higher TVL improves the perceived valuation and security of the ecosystem. This also suggests that there is an increased confidence as more users could be engaging in various DeFi applications in the ecosystem such as borrowing, lending, staking and other activities that contributes and adds utility towards the network. This underscores the importance of DeFi activities whereby a higher TVL often results in a positive impact on market capitalization for most ecosystem chains (Gudgeon *et al.*, 2020; Chiu *et al.*, 2022). Furthermore, trading volumes also respond positively to TVL shocks in some ecosystem chains which suggests that movements in TVL could drive trading activity, attracting investors that wish to capitalize on a thriving DeFi landscape (Chu *et al.*, 2023). However, other cryptocurrencies did not provide significant responses which suggests that their trading volumes are affected by external factors (Makridis *et al.*, 2023). Furthermore, the initial negative response followed by a positive correction in circulating supplies to TVL shocks imply that increased economic activity in DeFi applications initially locks up more tokens within these ecosystems, thus reducing circulating supply (Maouchi *et al.*, 2022). Therefore, TVL could be used as a key metric to ascertain the survivability and success of ecosystem chains as it captures certain market behavioral patterns within the cryptocurrency space.

7.4. Trading Volume, Stability and Liquidity

In order to comprehend the dynamics, liquidity, and stability of the cryptocurrency market, understanding trading volume is essential. When trading volume increases, it only indicates an increased trading activity without specifying whether it is caused by buying or selling pressures. Therefore, a robust and dynamic ecosystem's market capitalization should exhibit resilience towards trading volume shocks, maintaining a relatively stable valuation. The minor fluctuations observed in market capitalization responses to trading volume shocks followed by stabilization suggests that while an increased trading activity could cause volatility in the short term, market valuations are not altered fundamentally (Chu *et al.*, 2023). Hence, these ecosystem chains tend to retain value in the form of market capitalization. On the other hand, market capitalization has a strong positive influence over trading volumes. This implies that investors are attracted to cryptocurrencies that are increasing in value, leading to temporary surges in interest and trading activity driven by speculative interest. Bitcoin price possesses a strong positive influence over trading volume responses implying that Bitcoin could serve as a proxy which represents the cryptocurrency market sentiment. Conversely, altcoin trading volumes have little impact on the price of Bitcoin which reinforces Bitcoin's resistance to short term trading fluctuations in the altcoin market (Metelski and Sobieraj, 2022). Despite the common perception that retail investors follow influencers and actively react towards volatility, the responses suggest otherwise in which trading volume does not drive the market capitalization significantly compared to the other factors discussed. While circulating supply and total value locked tend to have minor effects in trading volume in most cryptocurrencies, there are exceptions. Total value locked shocks in BNB, ARB, OP, FTM exhibits a positive influence which suggest that trading activity does not necessarily boost DeFi engagement. Whereas a negative influence is recorded in AVAX, MATIC, OP, FTM for circulating supply shocks. These observations are a reminder to look beyond and consider other qualitative factors such as technological advancements for long term valuations (Makridis *et al.*, 2023).

7.5. DeFi Ecosystem Influence

As TVL exhibits a large positive influence over market capitalizations, the study can deduce that value locked within DeFi ecosystems can attract investors and drive-up investment into the underlying tokens. The influence of the DeFi ecosystems on Bitcoin is evident through the positive response of Bitcoin's price to TVL shocks in most cryptocurrencies. As more capital is locked within DeFi applications for staking, lending, and borrowing purposes, this serves as an overall market signal for positive growth, trust and investor confidence which ultimately influences the price of Bitcoin positively (Chiu *et al.*, 2022). This correlation underscores the importance of DeFi activities in shaping the overall crypto market sentiment and investor behavior (Maouchi *et al.*, 2022).

7.6. AVAX as an Outlier

Throughout the study, AVAX often does not provide significant results towards variable shocks as public interest could be relatively low for AVAX. This atypical response suggests that strong incentives are lacking for individuals to build or use any DeFi applications within the AVAX ecosystem. Furthermore, the wide confidence intervals observed in AVAX highlights the volatility and shows a less stable ecosystem. This implies that AVAX might not fulfil the role as a dynamic ecosystem as compared to its other counterparts, which affects its attractiveness and value proposition for developers, investors, and users.

7.7. Confidence Interval and Predictability

The varying confidence interval widths among cryptocurrencies highlight differing levels of predictability. Narrow confidence intervals show a more stable and predictable responses, suggesting that these cryptocurrencies are more matured and less influenced by factors such as speculative trading (Makridis *et al.*, 2023). In contrast, wider confidence intervals suggest higher volatility which reflects a more speculative and less stable cryptocurrency (Metelski and Sobieraj, 2022). Moreover, the narrow confidence intervals observed in TVL and Bitcoin price responses show that these metrics are largely consistent in producing reliable and stable results. These patterns reaffirm these metrics in offering valuable insights into different cryptocurrencies and their various ecosystems (Chiu *et al.*, 2022).

8. Endogeneity and Causality Concerns

The study acknowledges the empirical limitations of the VAR model in addressing endogeneity challenges and establishing causality. Endogeneity arises when independent explanatory variables have high correlations with the error term, which leads to bias and inconsistent estimates (Wooldridge, 2010). Causality concerns pertain to explanatory effects amongst variables which would be challenging to determine solely based on traditional models which only shows correlation and would be better substantiated with qualitative studies.

To address endogeneity concerns, the Granger Causality Tests were performed to isolate and find any evidence for predictive relationships between the variables (Kilian and Lütkepohl, 2017). The tests conducted revealed some directional insights. Firstly, market capitalization often displays significant causality from TVL and from BTC price in some cases, suggesting that movements in market capitalization could possibly be predicted by changes in TVL and BTCP. The study also finds that across most cryptocurrencies, TVL exhibit significant causality on other variables. BTC price also has significant influence over other variables especially for ETH, BNB and FTM. Lastly, CS and V hardly displays significant causality, suggesting a lesser role in predictions of the other variables. However, while the Granger Causality Test helps to address endogeneity concerns through the isolation of predictive relationships, it is not without limitations. For instance, omitted variable bias might not accounted for as the test assumes that all relevant information is captured. Furthermore, the method is sensitive to the selected lag length and might produce misleading results if it was not appropriately modelled. Despite these limitations, the Granger Causality Test reveal directional influence amongst variables and remains an invaluable tool for investigating preliminary causal inference (Figure 15).

The study had pre-determined the optimal number of lags. As discussed previously in the "Optimal Lag Pre-Estimation" section of the paper, the variables were regressed up to 7 lags and the cut off was made in ascending order upon reaching a lag number with statistical insignificance (Appendix A). After careful estimation considerations and robustness checks, a lag order of 1 was used to limit reverse causality effects.

ETH

Equation	Excluded	chi2	df	Prob>Chi2
pETHMC	pETHV	0.016	1	0.898
pETHMC	pETHCS	4.820	1	0.028
pETHMC	pETHTVL	57.558	1	0.000
pETHMC	pBTCP	5.620	1	0.018
pETHMC	ALL	67.957	4	0.000
pETHV	pETHMC	0.898	1	0.343
pETHV	pETHCS	0.317	1	0.573
pETHV	pETHTVL	0.515	1	0.473
pETHV	pBTCP	0.891	1	0.345
pETHV	ALL	2.159	4	0.706
pETHCS	pETHMC	0.725	1	0.394
pETHCS	pETHV	1.686	1	0.194
pETHCS	pETHTVL	12.314	1	0.000
pETHCS	pBTCP	4.984	1	0.026
pETHCS	ALL	18.319	4	0.001
pETHTVL	pETHMC	5.051	1	0.025
pETHTVL	pETHV	0.116	1	0.733
pETHTVL	pETHCS	4.517	1	0.034
pETHTVL	pBTCP	1.269	1	0.260
pETHTVL	ALL	19.812	4	0.001
pBTCP	pETHMC	18.095	1	0.000
pBTCP	pETHV	0.291	1	0.590
pBTCP	pETHCS	6.657	1	0.010
pBTCP	pETHTVL	32.824	1	0.000
pBTCP	ALL	44.765	4	0.000

TRX

Equation	Excluded	chi2	df	Prob>Chi2
pTRXMC	pTRXV	0.904	1	0.342
pTRXMC	pTRXCS	2.122	1	0.145
pTRXMC	pTRXTVL	19.392	1	0.000
pTRXMC	pBTCP	28.969	1	0.000
pTRXMC	ALL	35.515	4	0.000
pTRXV	pTRXMC	2.267	1	0.132
pTRXV	pTRXCS	0.246	1	0.620
pTRXV	pTRXTVL	0.533	1	0.465
pTRXV	pBTCP	1.445	1	0.229
pTRXV	ALL	3.635	4	0.458
pTRXCS	pTRXMC	0.064	1	0.801
pTRXCS	pTRXV	1.197	1	0.274
pTRXCS	pTRXTVL	2.685	1	0.101
pTRXCS	pBTCP	1.508	1	0.219
pTRXCS	ALL	4.279	4	0.370
pTRXTVL	pTRXMC	0.259	1	0.611
pTRXTVL	pTRXV	0.004	1	0.947
pTRXTVL	pTRXCS	0.951	1	0.329
pTRXTVL	pBTCP	5.710	1	0.017
pTRXTVL	ALL	6.748	4	0.150
pBTCP	pTRXMC	4.646	1	0.031
pBTCP	pTRXV	0.003	1	0.957
pBTCP	pTRXCS	0.065	1	0.799
pBTCP	pTRXTVL	27.299	1	0.000
pBTCP	ALL	29.363	4	0.000

BNB

Equation	Excluded	chi2	df	Prob>Chi2
pBNBMC	pBNBV	0.202	1	0.653
pBNBMC	pBNBCS	0.749	1	0.387
pBNBMC	pBNBTVL	78.251	1	0.000
pBNBMC	pBTCP	32.571	1	0.000
pBNBMC	ALL	90.574	4	0.000
pBNBV	pBNBMC	0.913	1	0.339
pBNBV	pBNBCS	0.439	1	0.507
pBNBV	pBNBTVL	3.551	1	0.059
pBNBV	pBTCP	4.453	1	0.035
pBNBV	ALL	12.524	4	0.014
pBNBCS	pBNBMC	4.182	1	0.041
pBNBCS	pBNBV	0.596	1	0.440
pBNBCS	pBNBTVL	6.673	1	0.010
pBNBCS	pBTCP	2.741	1	0.098
pBNBCS	ALL	14.918	4	0.005
pBNBTVL	pBNBMC	7.544	1	0.006
pBNBTVL	pBNBV	1.236	1	0.266
pBNBTVL	pBNBCS	0.426	1	0.514
pBNBTVL	pBTCP	0.135	1	0.713
pBNBTVL	ALL	11.842	4	0.019
pBTCP	pBNBMC	6.132	1	0.013
pBTCP	pBNBV	2.296	1	0.130
pBTCP	pBNBCS	0.026	1	0.872
pBTCP	pBNBTVL	9.828	1	0.002
pBTCP	ALL	14.434	4	0.006

SOL

Equation	Excluded	chi2	df	Prob>Chi2
pSOLMC	pSOLV	2.394	1	0.122
pSOLMC	pSOLCS	5.575	1	0.018
pSOLMC	pSOLTVL	12.213	1	0.000
pSOLMC	pBTCP	10.749	1	0.001
pSOLMC	ALL	29.337	4	0.000
pSOLV	pSOLMC	0.574	1	0.449
pSOLV	pSOLCS	0.047	1	0.828
pSOLV	pSOLTVL	0.478	1	0.489
pSOLV	pBTCP	9.085	1	0.003
pSOLV	ALL	10.544	4	0.032
pSOLCS	pSOLMC	0.047	1	0.828
pSOLCS	pSOLV	0.048	1	0.826
pSOLCS	pSOLTVL	2.023	1	0.155
pSOLCS	pBTCP	4.238	1	0.040
pSOLCS	ALL	7.461	4	0.113
pSOLTVL	pSOLMC	0.266	1	0.606
pSOLTVL	pSOLV	1.616	1	0.204
pSOLTVL	pSOLCS	1.655	1	0.198
pSOLTVL	pBTCP	2.262	1	0.133
pSOLTVL	ALL	5.115	4	0.276
pBTCP	pSOLMC	6.249	1	0.012
pBTCP	pSOLV	0.183	1	0.669
pBTCP	pSOLCS	0.771	1	0.380
pBTCP	pSOLTVL	9.572	1	0.002
pBTCP	ALL	12.236	4	0.016

ARB

Equation	Excluded	chi2	df	Prob>Chi2
pARBMC	pARBV	0.306	1	0.580
pARBMC	pARBCS	5.103	1	0.024
pARBMC	pARBTVL	22.078	1	0.000
pARBMC	pBTCP	5.149	1	0.023
pARBMC	ALL	22.363	4	0.000
pARBV	pARBMC	1.830	1	0.176
pARBV	pARBCS	2.754	1	0.097
pARBV	pARBTVL	2.611	1	0.106
pARBV	pBTCP	1.672	1	0.196
pARBV	ALL	7.825	4	0.098
pARBCS	pARBMC	2.228	1	0.136
pARBCS	pARBV	0.045	1	0.831
pARBCS	pARBTVL	0.206	1	0.650
pARBCS	pBTCP	8.610	1	0.003
pARBCS	ALL	9.811	4	0.044
pARBTVL	pARBMC	1.295	1	0.255
pARBTVL	pARBV	0.044	1	0.835
pARBTVL	pARBCS	0.220	1	0.639
pARBTVL	pBTCP	7.747	1	0.005
pARBTVL	ALL	8.037	4	0.090
pBTCP	pARBMC	2.164	1	0.141
pBTCP	pARBV	1.386	1	0.239
pBTCP	pARBCS	0.206	1	0.650
pBTCP	pARBTVL	23.593	1	0.000
pBTCP	ALL	37.462	4	0.000

AVAX

Equation	Excluded	chi2	df	Prob>Chi2
pAVAXMC	pAVAXV	0.087	1	0.768
pAVAXMC	pAVAXCS	1.147	1	0.284
pAVAXMC	pAVAXTVL	0.001	1	0.981
pAVAXMC	pBTCP	6.244	1	0.012
pAVAXMC	ALL	7.091	4	0.131
pAVAXV	pAVAXMC	0.120	1	0.729
pAVAXV	pAVAXCS	0.354	1	0.552
pAVAXV	pAVAXTVL	0.141	1	0.708
pAVAXV	pBTCP	5.808	1	0.016
pAVAXV	ALL	11.921	4	0.018
pAVAXCS	pAVAXMC	0.487	1	0.485
pAVAXCS	pAVAXV	0.073	1	0.787
pAVAXCS	pAVAXTVL	0.181	1	0.670
pAVAXCS	pBTCP	0.777	1	0.378
pAVAXCS	ALL	1.135	4	0.889
pAVAXTVL	pAVAXMC	7.578	1	0.006
pAVAXTVL	pAVAXV	1.286	1	0.257
pAVAXTVL	pAVAXCS	0.069	1	0.792
pAVAXTVL	pBTCP	0.690	1	0.406
pAVAXTVL	ALL	9.443	4	0.051
pBTCP	pAVAXMC	3.922	1	0.048
pBTCP	pAVAXV	1.493	1	0.222
pBTCP	pAVAXCS	0.253	1	0.615
pBTCP	pAVAXTVL	0.461	1	0.497
pBTCP	ALL	7.064	4	0.133

MATIC

Equation	Excluded	chi2	df	Prob>Chi2
pMATICMC	pMATICV	0.006	1	0.936
pMATICMC	pMATICCS	1.118	1	0.290
pMATICMC	pMATICTVL	47.487	1	0.000
pMATICMC	pBTCP	29.381	1	0.000
pMATICMC	ALL	61.535	4	0.000
pMATICV	pMATICMC	0.415	1	0.520
pMATICV	pMATICCS	1.665	1	0.197
pMATICV	pMATICTVL	0.244	1	0.621
pMATICV	pBTCP	2.797	1	0.094
pMATICV	ALL	4.246	4	0.374
pMATICCS	pMATICMC	2.272	1	0.132
pMATICCS	pMATICV	1.223	1	0.269
pMATICCS	pMATICTVL	0.313	1	0.576
pMATICCS	pBTCP	4.288	1	0.038
pMATICCS	ALL	6.252	4	0.181
pMATICTVL	pMATICMC	0.081	1	0.776
pMATICTVL	pMATICV	0.469	1	0.493
pMATICTVL	pMATICCS	1.103	1	0.294
pMATICTVL	pBTCP	6.496	1	0.011
pMATICTVL	ALL	8.891	4	0.064
pBTCP	pMATICMC	7.290	1	0.007
pBTCP	pMATICV	0.402	1	0.526
pBTCP	pMATICCS	1.701	1	0.192
pBTCP	pMATICTVL	31.662	1	0.000
pBTCP	ALL	34.487	4	0.000

OP

Equation	Excluded	chi2	df	Prob>Chi2
pOPMC	pOPV	1.545	1	0.214
pOPMC	pOPCS	2.490	1	0.115
pOPMC	pOPTVL	19.068	1	0.000
pOPMC	pBTCP	8.442	1	0.004
pOPMC	ALL	21.079	4	0.000
pOPV	pOPMC	0.035	1	0.851
pOPV	pOPCS	0.878	1	0.349
pOPV	pOPTVL	3.291	1	0.070
pOPV	pBTCP	0.046	1	0.830
pOPV	ALL	8.860	4	0.065
pOPCS	pOPMC	4.338	1	0.037
pOPCS	pOPV	3.062	1	0.080
pOPCS	pOPTVL	0.357	1	0.550
pOPCS	pBTCP	0.144	1	0.705
pOPCS	ALL	5.244	4	0.263
pOPTVL	pOPMC	2.184	1	0.139
pOPTVL	pOPV	0.239	1	0.625
pOPTVL	pOPCS	0.928	1	0.335
pOPTVL	pBTCP	3.507	1	0.061
pOPTVL	ALL	6.465	4	0.167
pBTCP	pOPMC	0.006	1	0.936
pBTCP	pOPV	2.142	1	0.143
pBTCP	pOPCS	0.227	1	0.633
pBTCP	pOPTVL	6.003	1	0.014
pBTCP	ALL	9.852	4	0.043

FTM

Equation	Excluded	chi2	df	Prob>Chi2
pFTMMC	pFTMV	0.115	1	0.735
pFTMMC	pFTMCS	1.260	1	0.262
pFTMMC	pFTMTVL	12.072	1	0.001
pFTMMC	pBTCP	3.948	1	0.047
pFTMMC	ALL	17.198	4	0.002
pFTMV	pFTMMC	0.000	1	0.986
pFTMV	pFTMCS	11.038	1	0.001
pFTMV	pFTMTVL	6.854	1	0.009
pFTMV	pBTCP	3.208	1	0.073
pFTMV	ALL	29.524	4	0.000
pFTMCS	pFTMMC	0.271	1	0.603
pFTMCS	pFTMV	8.236	1	0.004
pFTMCS	pFTMTVL	0.094	1	0.760
pFTMCS	pBTCP	8.012	1	0.005
pFTMCS	ALL	17.485	4	0.002
pFTMTVL	pFTMMC	0.315	1	0.574
pFTMTVL	pFTMV	0.477	1	0.490
pFTMTVL	pFTMCS	1.207	1	0.272
pFTMTVL	pBTCP	2.136	1	0.144
pFTMTVL	ALL	3.726	4	0.444
pBTCP	pFTMMC	0.063	1	0.802
pBTCP	pFTMV	2.037	1	0.153
pBTCP	pFTMCS	0.470	1	0.493
pBTCP	pFTMTVL	4.582	1	0.032
pBTCP	ALL	7.590	4	0.108

Figure 15: Granger Causality Test Results for all Five Variables

This ensures that the study meets adequate appropriateness and dynamic completeness (Abdallah *et al.*, 2015; Imbens and Rubin, 2015).

As endogeneity and causality concerns are appropriately addressed, the study not only offers evidence for casual relationships, but also attempts to propose certain causal effects explanations.

8.1. Granger Causality Test – Directional Influence Explanations

Based on the findings from the Granger Causality Tests conducted (Figure 15), the study could pinpoint certain directional influence between certain variables allowing for interpretations as potential proxy indicators. The study finds that market capitalizations exhibits significant causality from both TVL and BTC price, suggesting that changes in TVL and BTCP can potentially predict movements in market capitalizations. Moreover, TVL also exhibits significant causality on other variables. Furthermore, BTC price exhibits strong influence over other variables, which is prevalent in ETH, BNB and FTM. Unfortunately, CS and V hardly show much causality implying a subdued role in predictions.

8.1.1. Market Capitalization Response to TVL and BTCP Impulses

The Granger causality test results highlight notable directional influences among key cryptocurrency variables. Market Capitalization (MC) shows significant responsiveness to Total Value Locked (TVL) and Bitcoin Price (BTCP) impulses. This suggests that changes in TVL and BTCP can predict market capitalization shifts. TVL, which measures the capital locked in DeFi platforms, serves as an indicator of investor confidence and ecosystem health. An increase in TVL typically signals vigorous economic activity within the blockchain, boosting market capitalization (Gudgeon *et al.*, 2020). Similarly, BTCP, as the leading cryptocurrency, has a substantial impact on the broader market. Positive changes in BTCP often result in increased market capitalization across various cryptocurrencies, highlighting Bitcoin's key role in influencing market trends and investor sentiment (Chiu *et al.*, 2022).

8.1.2. TVL's Influence on Other Variables

Further analysis from the Granger causality test indicates that TVL strongly influences other variables within the cryptocurrency ecosystem. This finding underscores TVL's pivotal role in driving market dynamics. When TVL increases, reflecting more capital in DeFi protocols, it not only boosts liquidity but also enhances trading volumes and market confidence. This causative effect underscores TVL's importance as a key metric for assessing ecosystem health and predicting broader market movements (Chu *et al.*, 2023). Thus, investors and analysts can use TVL to gauge the underlying strength and potential growth of the cryptocurrency market, making it a crucial indicator for strategic decision-making (Schär, 2020).

8.1.3. BTCP's Influence on in ETH, BNB, and FTM

The Granger causality test also shows that BTCP significantly influences Ethereum (ETH), Binance Coin (BNB), and Fantom (FTM). This directional influence implies that changes in Bitcoin's price can result in notable shifts within the market dynamics of these altcoins. For Ethereum, a positive shock from Bitcoin can enhance its market capitalization, trading volume, and overall market presence. Similarly, Binance Coin, which is integral to the Binance ecosystem, shows a strong reaction to Bitcoin price movements, reflecting its sensitivity to broader market trends (Makridis *et al.*, 2023). Fantom, a newer DeFi platform, also demonstrates strong responsiveness to Bitcoin's price, indicating that market activity and investor confidence in FTM are significantly influenced by Bitcoin's performance (Maouchi *et al.*, 2022). These findings highlight the interconnected nature of the cryptocurrency market, where Bitcoin's performance can cascade effects on other major cryptocurrencies (Gandal and Halaburda, 2016).

9. Variance (Forecast Error) Decomposition

Variance decomposition analysis shows the percentage that can be explained by a shock variable in forecasting the dependent variable overtime. It is a statistical technique that helps to deconstruct and isolate the amount of variability in the dependent variable that can be attributed to shocks within its system versus the other variable shocks in the system. Essentially, these findings underlines both intrinsic and extrinsic elements when forecasting the dynamics of the ecosystem chain valuation metrics (Zaefarian *et al.*, 2022).

For market capitalization responses, most cryptocurrencies respond positively to BTCP shocks. Only ETH does not have significant response to BTCP. Except for TRX, AVAX, most cryptocurrency market capitalizations respond positively to TVL shocks. Both CS and V shocks does not induce significant responses (Figure 16). Regarding trading volume, a variety of responses are observed. Firstly, BNB, SOL, AVAX, MATIC responds positively to BTCP shocks, while only MATIC, FTM responds positively to CS shocks. The trading volume

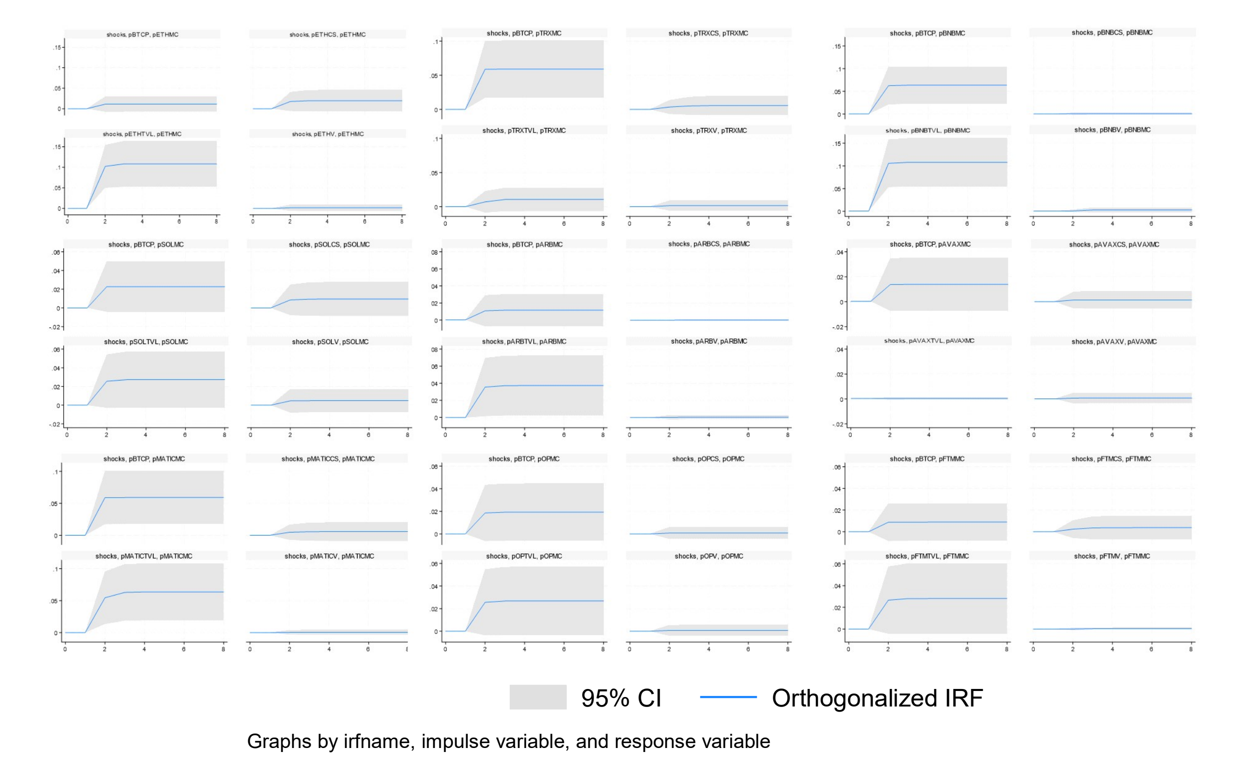

Figure 16: Variance Decomposition Results (Market Capitalization Responses to Shocks)

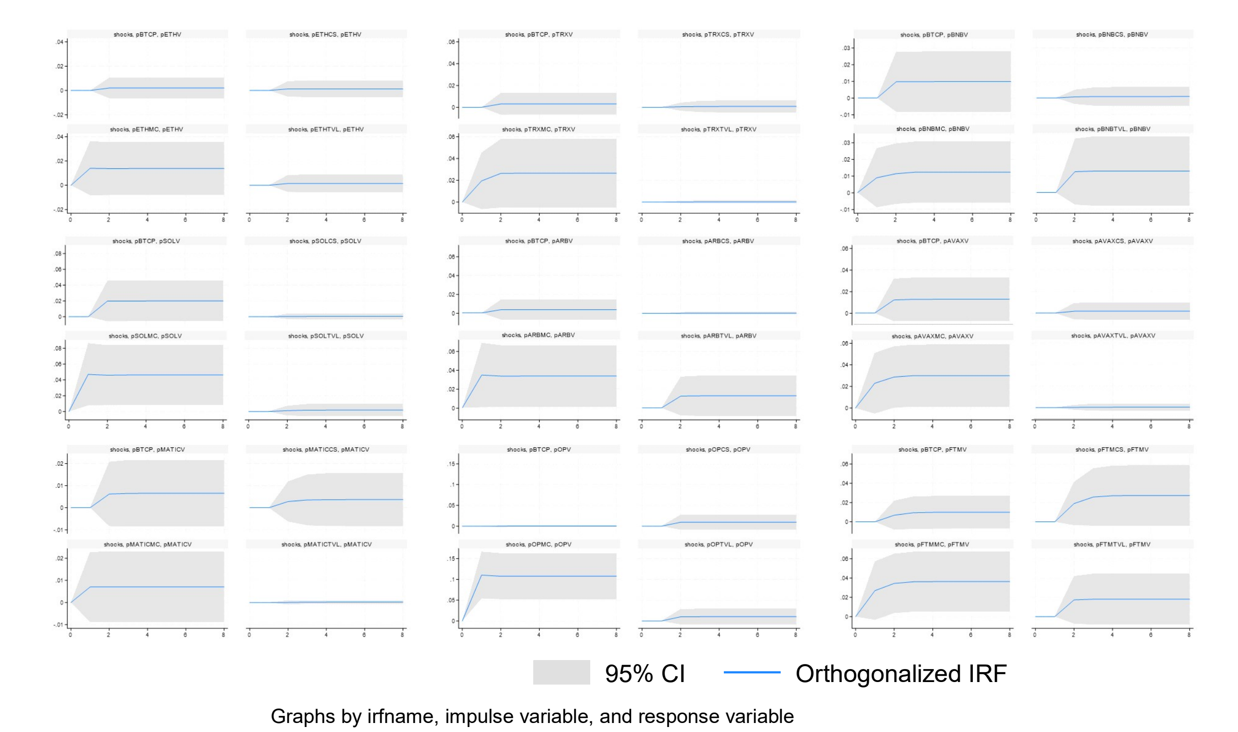

Figure 17: Variance Decomposition Results (Trading Volume Responses to Shocks)

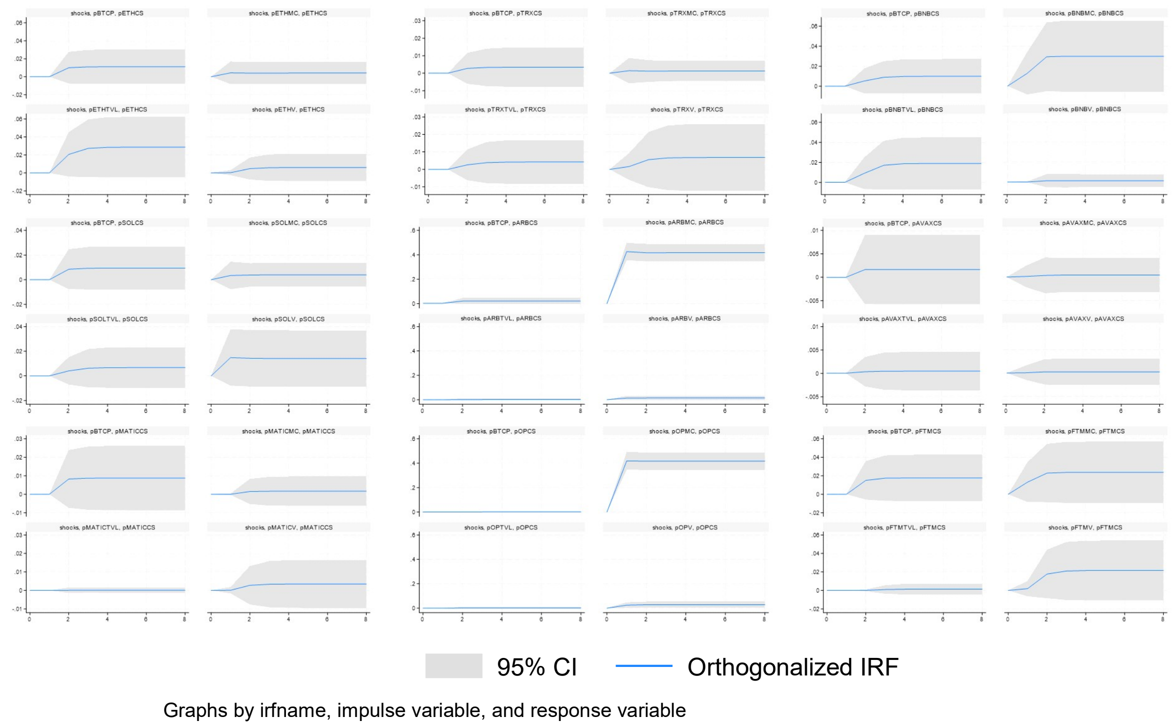

Figure 18: Variance Decomposition Results (Circulating Supply Responses to Shocks)

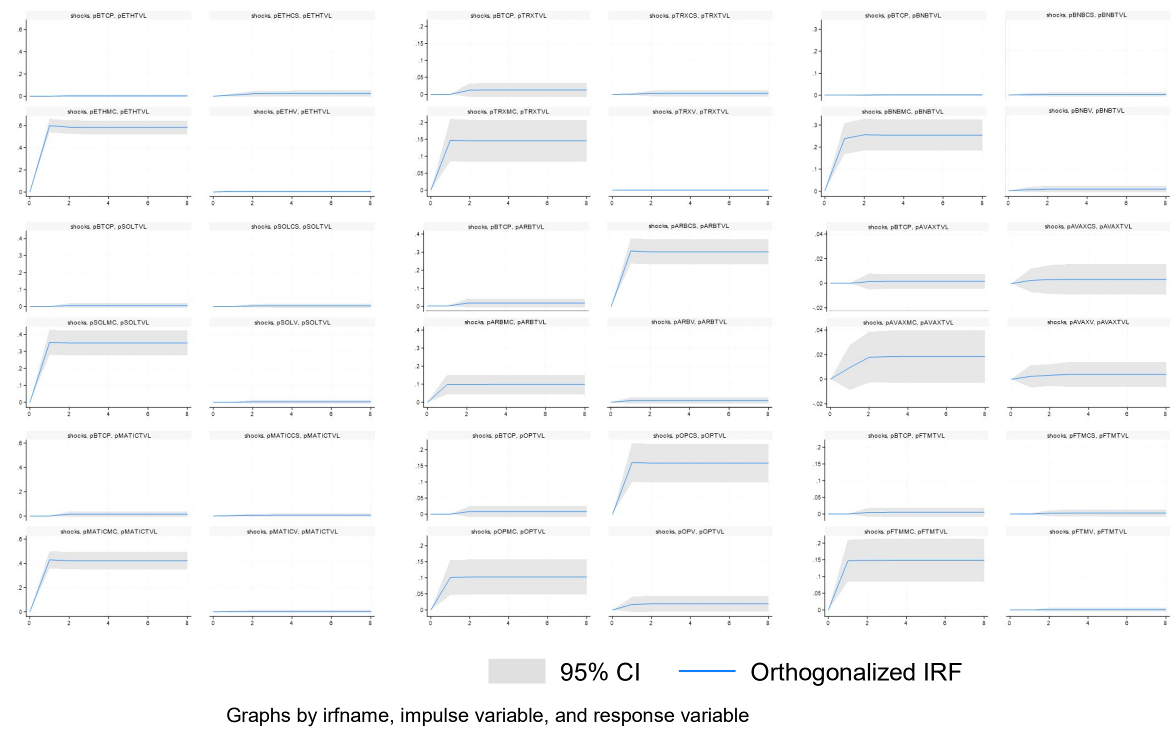

Figure 19: Variance Decomposition Results (Total Value Locked Responses to Shocks)

responds positively to MC shocks in all cryptocurrencies. Lastly, only BNB, ARB, FTM responds positively to TVL shocks (Figure 17). For circulating supply, the graphs show that most cryptocurrencies have slight responses to BTCP shocks. In some instances, only ETH, BNB, responds positively to TVL shocks while only SOL, FTM responds positively to V shocks. A notable observation is that only OP, ARB have a large positive

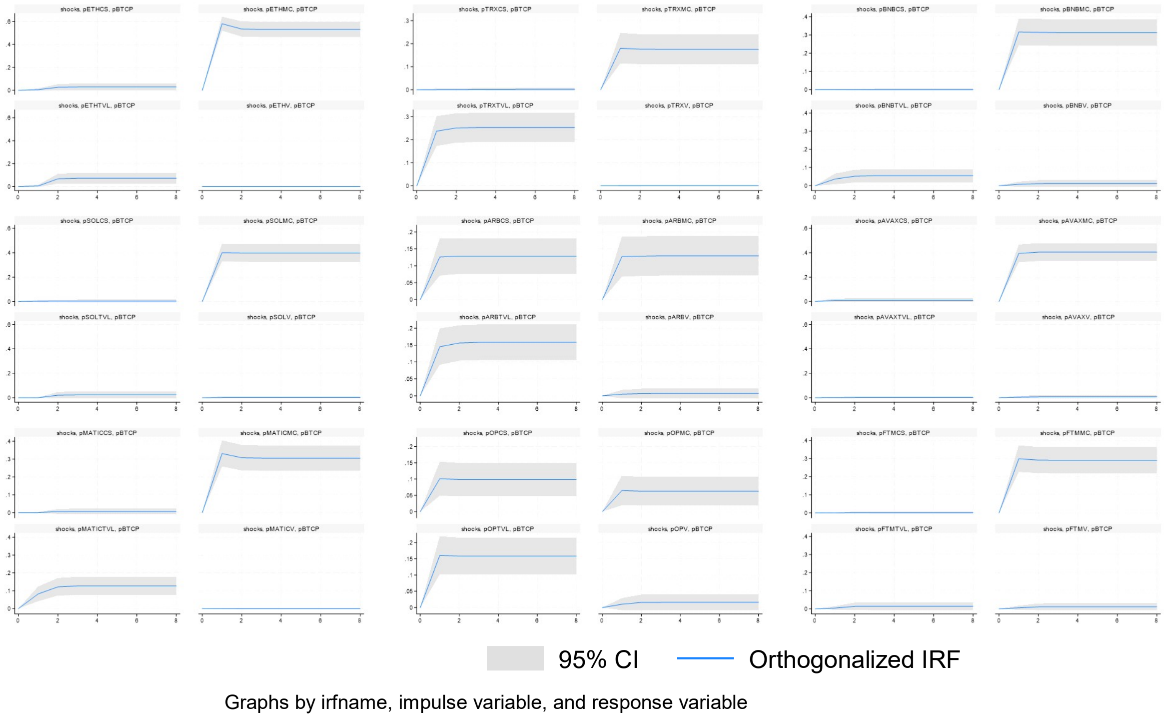

Figure 20: Variance Decomposition Results (Bitcoin Price Responses to Shocks)

response (0.4) to MC shocks (Figure 18). For total value locked, all cryptocurrencies respond positively to MC shocks. Only ARB, OP responds positively to CS shocks (Figure 19). Bitcoin price responds positively to MC shocks for all cryptocurrencies and to TVL shocks in TRX, ARB, MATIC, OP. Minimal responses are observed for CS and V shocks in altcoins to the price of Bitcoin (Figure 20).

Based on the results of the variance decomposition, changes in Total Value Locked (TVL) could be significantly explained by market capitalizations in ETH, BNB, SOL and MATIC with explanatory percentages that exceed 25%. This implies that investors may view market capitalization as an indicator for stability, trustworthiness, and potential rewards. As such, investors might contribute into the DeFi ecosystem through various methods such as borrowing, lending, or staking, resulting in a positive reflection through the TVL. Additionally, circulating supply shocks in ARB and OP contributes towards changes in TVL with an approximate of 30% and 15% respectively. This suggests that in newer cryptocurrencies, inflation has a stronger influence on investor confidence and their likelihood to lock up their tokens in these ecosystems as compared to more matured ecosystems. Bitcoin price (BTCP) changes are also significantly influenced by market capitalization shocks in ETH, BNB, SOL, AVAX, MATIC and FTM with significant explanatory percentages exceeding 25%. This highlights how intertwined the altcoins are with Bitcoin, which could be due to the large volume of Bitcoin trading pairs on CEXs and DEXs. Interestingly in TRX, TVL shocks also explain about 25% of changes in BTCP. This could be because one of the most common and widely used stable coin USDT is built on TRX's network. In a similar manner to BTC, USDT also have a wide variety of trading pairs on CEXs, hence, changes in TRX TVL could relate to increases or decreases in USDT for trading on the markets, resulting in shifts in BTCP. Unfortunately, responses of Market Capitalizations (MC) and trading Volume (V) are rather self-contained and are not well explained by shocks from other variables as their explanatory power remains below ~20%. This implies that internal dynamic shocks by themselves are the primary reason for their movements. While most cryptocurrencies Circulating Supply (CS) are largely unexplainable by other variables, they can be attributed towards market capitalizations in ARB and OP with an approximate of ~40%. This could be caused by the data aggregators not being able to accurately account for all the available tokens in circulating supply for these newer cryptocurrencies. These results can be found in Figure 21.

10. Conclusion

In summary, while the study provides comprehensive analysis over the interactions between key valuation metrics: market capitalization, trading volume, circulating supply, total value locked and Bitcoin price, the need for continued research is emphasized. Future studies ought to include a more extensive range of cryptocurrencies, integrate qualitative considerations, extend the investigative data period and consider external macroeconomic factors. By addressing these issues, academics and investors can better comprehend and navigate the complex and ever-changing cryptocurrency landscape. In the future, forecast accuracy of cryptocurrencies would improve drastically for the betterment of all stakeholders.

11. Limitations and Suggestions for Future Research

While our study provides insightful information on the relationships between key valuation metrics of these cryptocurrency ecosystems, there are limitations. While the cryptocurrency industry is vast and diverse, the concentrated focus on a select few cryptocurrencies could result in certain bias. Future studies could encompass a wider scope to include newer or lesser-known cryptocurrencies. Otherwise, exploring a separate sub-classification such as oracles or aggregators could yield different results and perspectives.

As cryptocurrencies are extremely volatile assets, a different time horizon could be investigated. Daily data points are currently used in this study whereby future studies could investigate shorter time periods in hourly data. This would consider a different lag order as well which might result in better models for these digital assets. Alternatively, analyzing crypto data over extended time periods might conceal short term anomalies and reveal long term patterns. An update of the study with renewed future data sets could also help determine whether these metrics continue to hold up or not. Understanding how these assets behave would be essential in forecasting movements in markets and secure long-term stability and survivability in the ever-changing crypto landscape.

While the study includes key quantitative variables such as changes in the market capitalization, trading volume, circulating supply, total value locked, and price of Bitcoin, these measurements might not be fully representative of the crypto valuations. External macroeconomic factors such as regulatory shifts, and political developments were not considered in this study. These factors could have had significant influence on investor behavior and cryptocurrency valuations. Furthermore, online social media sentiments reflected through Twitter, Reddit or Youtube could also have had certain impacts. Incorporating these qualitative factors could help provide a more holistic understanding of these cryptocurrency valuations. It might be beneficial for future research to adopt a mixed-method approach that synthesizes both quantitative and qualitative data to polish and strengthen the in-depth analysis.

Moreover, the study did not place a large emphasis on technological advancements within each ecosystem chain. Innovations that enhance security and change protocols might offer new use cases and propositions. This could significantly impact investment behaviors affecting these valuation metrics. Future researchers could examine the impact of these technological developments in shaping cryptocurrency markets. This would further improve potential forecasts and predictions fundamentally.

Lastly, future research could utilize different statistical models such as an Ordinary Least Squares (OLS) or a Vector Error Correction Model (VECM) to examine the relationships between cryptocurrency metrics. The VECM can be used to model non-stationary data which could be prevalent with crypto data sets. These models could result in better fits revealing more precise results and findings.

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Appendix A

A.1: Determining Optimal Lags through Varsoc

. varsoc pETHMC pETHV pETHCS pETHTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4830.04				7.2e-17	-22.9764	-22.9574	-22.9283
1	4919.42	178.76	25	0.000	5.3e-17	-23.2829	-23.1689*	-22.9943*
2	4944.62	50.405*	25	0.002	5.3e-17*	-23.2839*	-23.0748	-22.7548
3	4959.57	29.893	25	0.228	5.6e-17	-23.236	-22.9319	-22.4665
4	4974.25	29.36	25	0.249	5.9e-17	-23.1869	-22.7877	-22.1768
5	4991.39	34.297	25	0.102	6.1e-17	-23.1495	-22.6552	-21.8989
6	5000.42	18.045	25	0.840	6.6e-17	-23.0734	-22.4841	-21.5824
7	5016.05	31.274	25	0.180	6.9e-17	-23.0288	-22.3444	-21.2973

* optimal lag
Endogenous: **pETHMC pETHV pETHCS pETHTVL pBTCP**
Exogenous: **_cons**

. varsoc pTRXMC pTRXV pTRXCS pTRXTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	5366.11				5.6e-18	-25.5291	-25.5101	-25.481
1	5453.32	174.41	25	0.000	4.2e-18	-25.8253	-25.7113	-25.5367*
2	5514.56	122.48	25	0.000	3.5e-18*	-25.9979*	-25.7888*	-25.4688
3	5533.32	37.536	25	0.051	3.6e-18	-25.9682	-25.664	-25.1986
4	5550.09	33.524	25	0.118	3.8e-18	-25.929	-25.5298	-24.9189
5	5571.11	42.057	25	0.018	3.8e-18	-25.9101	-25.4158	-24.6595
6	5585.96	29.69	25	0.236	4.0e-18	-25.8617	-25.2724	-24.3707
7	5607.04	42.159*	25	0.017	4.1e-18	-25.843	-25.1587	-24.1115

* optimal lag
Endogenous: **pTRXMC pTRXV pTRXCS pTRXTVL pBTCP**
Exogenous: **_cons**

. varsoc pBNBMC pBNBV pBNBCS pBNBTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4586.34				2.3e-16	-21.8159	-21.7969	-21.7678
1	4706.34	240	25	0.000	1.5e-16	-22.2683	-22.1542*	-21.9797*
2	4742.09	71.494	25	0.000	1.4e-16	-22.3195	-22.1103	-21.7904
3	4773.84	63.499	25	0.000	1.4e-16*	-22.3516*	-22.0474	-21.582
4	4798.49	49.316	25	0.003	1.4e-16	-22.35	-21.9508	-21.3399
5	4818.66	40.33	25	0.027	1.4e-16	-22.327	-21.8327	-21.0764
6	4838.02	38.728*	25	0.039	1.4e-16	-22.3001	-21.7108	-20.8091
7	4851.34	26.632	25	0.375	1.5e-16	-22.2445	-21.5601	-20.5129

* optimal lag
Endogenous: **pBNBMC pBNBV pBNBCS pBNBTVL pBTCP**
Exogenous: **_cons**

. varsoc pSOLMC pSOLV pSOLCS pSOLTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4207				1.4e-15	-20.0095	-19.9905	-19.9614*
1	4280.59	147.19	25	0.000	1.1e-15*	-20.2409*	-20.1269*	-19.9523
2	4301.98	42.775	25	0.015	1.1e-15	-20.2237	-20.0146	-19.6946
3	4315.33	26.699	25	0.371	1.2e-15	-20.1682	-19.8641	-19.3987
4	4337.32	43.978	25	0.011	1.2e-15	-20.1539	-19.7547	-19.1438
5	4359.1	43.549*	25	0.012	1.2e-15	-20.1385	-19.6443	-18.888
6	4373.69	29.189	25	0.256	1.3e-15	-20.089	-19.4997	-18.598
7	4385.59	23.801	25	0.531	1.4e-15	-20.0266	-19.3422	-18.2951

* optimal lag
Endogenous: **pSOLMC pSOLV pSOLCS pSOLTVL pBTCP**
Exogenous: **_cons**

. varsoc pARBMC pARBV pARBCS pARBTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	3296.49				1.1e-13	-15.6737	-15.6547	-15.6256*
1	3358.3	123.62	25	0.000	9.0e-14	-15.849	-15.735*	-15.5604
2	3385.06	53.537	25	0.001	8.9e-14*	-15.8574*	-15.6483	-15.3284
3	3397.25	24.362	25	0.499	9.5e-14	-15.7964	-15.4922	-15.0268
4	3416.14	37.78*	25	0.049	9.8e-14	-15.7673	-15.3681	-14.7572
5	3434.65	37.037	25	0.057	1.0e-13	-15.7364	-15.2422	-14.4859
6	3445.67	22.03	25	0.634	1.1e-13	-15.6699	-15.0805	-14.1788
7	3463.51	35.677	25	0.077	1.1e-13	-15.6358	-14.9514	-13.9042

* optimal lag
Endogenous: **pARBMC pARBV pARBCS pARBTVL pBTCP**
Exogenous: **_cons**

. varsoc pAVAXMC pAVAXV pAVAXCS pAVAXTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	3599.4				2.5e-14	-17.1162	-17.0972	-17.0681*
1	3657.44	116.08	25	0.000	2.2e-14	-17.2735	-17.1595*	-16.9849
2	3688.19	61.501	25	0.000	2.1e-14*	-17.3009*	-17.0918	-16.7718
3	3708.22	40.059	25	0.029	2.2e-14	-17.2772	-16.9731	-16.5077
4	3729.95	43.459	25	0.012	2.2e-14	-17.2617	-16.8625	-16.2516
5	3744.03	28.15	25	0.301	2.3e-14	-17.2097	-16.7154	-15.9591
6	3761.95	35.855	25	0.074	2.4e-14	-17.176	-16.5866	-15.6849
7	3781.43	38.953*	25	0.037	2.5e-14	-17.1497	-16.4653	-15.4181

* optimal lag
Endogenous: **pAVAXMC pAVAXV pAVAXCS pAVAXTVL pBTCP**
Exogenous: **_cons**

. varsoc pMATICMC pMATICV pMATICCS pMATICTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4675.56				1.5e-16	-22.2407	-22.2217	-22.1926
1	4767.81	184.51	25	0.000	1.1e-16	-22.561	-22.447	-22.2724*
2	4813.33	91.035	25	0.000	9.9e-17	-22.6587	-22.4496*	-22.1296
3	4836.49	46.327	25	0.006	1.0e-16	-22.65	-22.3458	-21.8804
4	4863.98	54.962	25	0.000	9.9e-17*	-22.6618*	-22.2626	-21.6517
5	4880.04	32.139	25	0.154	1.0e-16	-22.6193	-22.125	-21.3687
6	4893.01	25.926	25	0.412	1.1e-16	-22.5619	-21.9726	-21.0709
7	4912.29	38.554*	25	0.041	1.1e-16	-22.5347	-21.8503	-20.8032

* optimal lag
Endogenous: **pMATICMC pMATICV pMATICCS pMATICTVL pBTCP**
Exogenous: **_cons**

. varsoc pOPMC pOPV pOPCS pOPTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	3194.18				1.7e-13	-15.1866	-15.1676*	-15.1385*
1	3227.81	67.259	25	0.000	1.7e-13*	-15.2277*	-15.1136	-14.9391
2	3249.11	42.601	25	0.015	1.7e-13	-15.2101	-15.0009	-14.681
3	3263.6	28.983	25	0.265	1.8e-13	-15.16	-14.8558	-14.3904
4	3276.14	25.076	25	0.458	1.9e-13	-15.1007	-14.7014	-14.0906
5	3297.18	42.081*	25	0.018	1.9e-13	-15.0818	-14.5875	-13.8313
6	3309.14	23.922	25	0.524	2.1e-13	-15.0197	-14.4304	-13.5287
7	3320.09	21.891	25	0.642	2.2e-13	-14.9528	-14.2684	-13.2213

* optimal lag
Endogenous: **pOPMC pOPV pOPCS pOPTVL pBTCP**
Exogenous: **_cons**

. varsoc pFTMMC pFTMV pFTMCS pFTMTVL pBTCP, maxlag(7)

Lag-order selection criteria

Sample: **8** thru **427** Number of obs = **420**

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	3857.33				7.4e-15	-18.3444	-18.3254	-18.2963
1	3951.78	188.89	25	0.000	5.3e-15	-18.6751	-18.5611*	-18.3865*
2	3984.46	65.372	25	0.000	5.1e-15	-18.7117	-18.5026	-18.1827
3	4015.79	62.647	25	0.000	5.0e-15	-18.7418	-18.4377	-17.9723
4	4041.02	50.471	25	0.002	5.0e-15*	-18.743*	-18.3437	-17.7329
5	4057.95	33.852	25	0.111	5.2e-15	-18.7045	-18.2102	-17.454
6	4083.12	50.349	25	0.002	5.2e-15	-18.7054	-18.116	-17.2143
7	4104.23	42.213*	25	0.017	5.3e-15	-18.6868	-18.0024	-16.9553

* optimal lag
Endogenous: **pFTMMC pFTMV pFTMCS pFTMTVL pBTCP**
Exogenous: **_cons**

Appendix B

B.1: Variance Decomposition Table Results (Shocks)

ETH	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.014	0.000	0.000	0.000	0.986	0.004	0.000	0.000	0.000	0.996	0.598	0.005	0.010	0.000	0.387	0.581	0.000	0.006	0.005	0.408
2	0.002	0.018	0.102	0.011	0.867	0.014	0.001	0.001	0.002	0.982	0.004	0.005	0.021	0.010	0.960	0.585	0.005	0.021	0.003	0.386	0.535	0.000	0.027	0.067	0.371
3	0.002	0.020	0.108	0.011	0.859	0.014	0.001	0.001	0.002	0.982	0.004	0.006	0.027	0.011	0.952	0.582	0.005	0.024	0.003	0.386	0.530	0.000	0.029	0.072	0.369
4	0.002	0.020	0.108	0.011	0.859	0.014	0.001	0.001	0.002	0.982	0.004	0.006	0.028	0.011	0.951	0.582	0.005	0.024	0.003	0.386	0.530	0.000	0.029	0.072	0.369
5	0.002	0.020	0.108	0.011	0.859	0.014	0.001	0.001	0.002	0.982	0.004	0.006	0.029	0.011	0.950	0.582	0.005	0.024	0.003	0.386	0.530	0.000	0.029	0.072	0.369
6	0.002	0.020	0.108	0.011	0.859	0.014	0.001	0.001	0.002	0.982	0.004	0.006	0.029	0.011	0.950	0.582	0.005	0.024	0.003	0.386	0.530	0.000	0.029	0.072	0.369
7	0.002	0.020	0.108	0.011	0.859	0.014	0.001	0.001	0.002	0.982	0.004	0.006	0.029	0.011	0.950	0.582	0.005	0.024	0.003	0.386	0.530	0.000	0.029	0.072	0.369
8	0.002	0.020	0.108	0.011	0.859	0.014	0.001	0.001	0.002	0.982	0.004	0.006	0.029	0.011	0.950	0.582	0.005	0.024	0.003	0.386	0.530	0.000	0.029	0.072	0.369

TRX	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.019	0.000	0.000	0.000	0.981	0.001	0.002	0.000	0.000	0.997	0.147	0.000	0.000	0.000	0.853	0.180	0.000	0.000	0.238	0.582
2	0.002	0.003	0.007	0.059	0.929	0.026	0.000	0.000	0.003	0.971	0.001	0.006	0.003	0.003	0.987	0.145	0.000	0.002	0.012	0.841	0.176	0.000	0.001	0.251	0.572
3	0.002	0.005	0.011	0.059	0.923	0.026	0.001	0.000	0.003	0.970	0.001	0.007	0.004	0.003	0.985	0.145	0.000	0.003	0.013	0.839	0.175	0.000	0.001	0.253	0.571
4	0.002	0.006	0.011	0.059	0.922	0.026	0.001	0.000	0.003	0.970	0.001	0.007	0.004	0.003	0.985	0.145	0.000	0.003	0.013	0.839	0.175	0.000	0.002	0.253	0.570
5	0.002	0.006	0.011	0.059	0.922	0.026	0.001	0.000	0.003	0.970	0.001	0.007	0.004	0.003	0.985	0.145	0.000	0.003	0.013	0.839	0.175	0.000	0.002	0.253	0.570
6	0.002	0.006	0.011	0.059	0.922	0.026	0.001	0.000	0.003	0.970	0.001	0.007	0.004	0.003	0.985	0.145	0.000	0.003	0.013	0.839	0.175	0.000	0.002	0.253	0.570
7	0.002	0.006	0.011	0.059	0.922	0.026	0.001	0.000	0.003	0.970	0.001	0.007	0.004	0.003	0.985	0.145	0.000	0.003	0.013	0.839	0.175	0.000	0.002	0.253	0.570
8	0.002	0.006	0.011	0.059	0.922	0.026	0.001	0.000	0.003	0.970	0.001	0.007	0.004	0.003	0.985	0.145	0.000	0.003	0.013	0.839	0.175	0.000	0.002	0.253	0.570

BNB	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.009	0.000	0.000	0.000	0.991	0.013	0.000	0.000	0.000	0.987	0.238	0.005	0.002	0.000	0.755	0.317	0.008	0.000	0.037	0.638
2	0.000	0.000	0.106	0.062	0.832	0.011	0.001	0.013	0.010	0.965	0.029	0.001	0.009	0.005	0.956	0.255	0.008	0.003	0.000	0.734	0.314	0.012	0.000	0.052	0.622
3	0.002	0.000	0.108	0.063	0.827	0.012	0.001	0.013	0.010	0.964	0.030	0.001	0.017	0.009	0.943	0.254	0.008	0.003	0.002	0.733	0.313	0.013	0.000	0.055	0.619
4	0.003	0.000	0.108	0.063	0.826	0.012	0.001	0.013	0.010	0.964	0.030	0.001	0.019	0.010	0.940	0.254	0.008	0.003	0.002	0.733	0.313	0.013	0.000	0.055	0.619
5	0.003	0.000	0.108	0.063	0.826	0.012	0.001	0.013	0.010	0.964	0.030	0.001	0.019	0.010	0.940	0.254	0.008	0.003	0.002	0.733	0.313	0.013	0.000	0.055	0.619
6	0.003	0.000	0.108	0.063	0.826	0.012	0.001	0.013	0.010	0.964	0.030	0.001	0.019	0.010	0.940	0.254	0.008	0.003	0.002	0.733	0.313	0.013	0.000	0.055	0.619
7	0.003	0.000	0.108	0.063	0.826	0.012	0.001	0.013	0.010	0.964	0.030	0.001	0.019	0.010	0.940	0.254	0.008	0.003	0.002	0.733	0.313	0.013	0.000	0.055	0.619
8	0.003	0.000	0.108	0.063	0.826	0.012	0.001	0.013	0.010	0.964	0.030	0.001	0.019	0.010	0.940	0.254	0.008	0.003	0.002	0.733	0.313	0.013	0.000	0.055	0.619

SOL	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.047	0.000	0.000	0.000	0.953	0.003	0.015	0.000	0.000	0.982	0.353	0.000	0.000	0.000	0.647	0.401	0.002	0.002	0.000	0.595
2	0.005	0.009	0.026	0.023	0.937	0.046	0.000	0.001	0.020	0.933	0.004	0.014	0.004	0.008	0.970	0.350	0.003	0.003	0.005	0.639	0.398	0.003	0.004	0.020	0.575
3	0.005	0.009	0.027	0.023	0.936	0.046	0.000	0.002	0.020	0.932	0.004	0.014	0.006	0.009	0.967	0.350	0.003	0.004	0.005	0.638	0.397	0.003	0.004	0.023	0.573
4	0.005	0.010	0.027	0.023	0.935	0.046	0.000	0.002	0.020	0.932	0.004	0.014	0.007	0.009	0.966	0.350	0.003	0.004	0.005	0.638	0.397	0.003	0.004	0.023	0.573
5	0.005	0.010	0.027	0.023	0.935	0.046	0.000	0.002	0.020	0.932	0.004	0.014	0.007	0.009	0.966	0.350	0.003	0.004	0.005	0.638	0.397	0.003	0.004	0.023	0.573
6	0.005	0.010	0.027	0.023	0.935	0.046	0.000	0.002	0.020	0.932	0.004	0.014	0.007	0.009	0.966	0.350	0.003	0.004	0.005	0.638	0.397	0.003	0.004	0.023	0.573
7	0.005	0.010	0.027	0.023	0.935	0.046	0.000	0.002	0.020	0.932	0.004	0.014	0.007	0.009	0.966	0.350	0.003	0.004	0.005	0.638	0.397	0.003	0.004	0.023	0.573
8	0.005	0.010	0.027	0.023	0.935	0.046	0.000	0.002	0.020	0.932	0.004	0.014	0.007	0.009	0.966	0.350	0.003	0.004	0.005	0.638	0.397	0.003	0.004	0.023	0.573

ARB	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.035	0.000	0.000	0.000	0.965	0.426	0.014	0.000	0.000	0.560	0.098	0.009	0.306	0.000	0.587	0.127	0.005	0.126	0.145	0.597
2	0.000	0.000	0.036	0.011	0.953	0.033	0.000	0.013	0.003	0.951	0.417	0.014	0.002	0.018	0.549	0.098	0.009	0.301	0.016	0.576	0.129	0.006	0.129	0.156	0.580
3	0.000	0.000	0.037	0.011	0.952	0.034	0.000	0.013	0.004	0.949	0.417	0.015	0.002	0.018	0.548	0.098	0.009	0.301	0.016	0.576	0.130	0.007	0.129	0.158	0.576
4	0.000	0.000	0.038	0.011	0.951	0.034	0.000	0.013	0.004	0.949	0.417	0.015	0.002	0.018	0.548	0.098	0.009	0.301	0.016	0.576	0.130	0.007	0.129	0.158	0.576
5	0.000	0.000	0.038	0.011	0.951	0.034	0.000	0.013	0.004	0.949	0.417	0.015	0.002	0.018	0.548	0.098	0.009	0.301	0.016	0.576	0.130	0.007	0.129	0.158	0.576
6	0.000	0.000	0.038	0.011	0.951	0.034	0.000	0.013	0.004	0.949	0.417	0.015	0.002	0.018	0.548	0.098	0.009	0.301	0.016	0.576	0.130	0.007	0.129	0.158	0.576
7	0.000	0.000	0.038	0.011	0.951	0.034	0.000	0.013	0.004	0.949	0.417	0.015	0.002	0.018	0.548	0.098	0.009	0.301	0.016	0.576	0.130	0.007	0.129	0.158	0.576
8	0.000	0.000	0.038	0.011	0.951	0.034	0.000	0.013	0.004	0.949	0.417	0.015	0.002	0.018	0.548	0.098	0.009	0.301	0.016	0.576	0.130	0.007	0.129	0.158	0.576

AVAX	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.023	0.000	0.000	0.000	0.977	0.000	0.000	0.000	0.000	1.000	0.009	0.002	0.003	0.000	0.986	0.394	0.004	0.010	0.001	0.591
2	0.001	0.001	0.000	0.014	0.984	0.029	0.002	0.000	0.012	0.957	0.000	0.000	0.000	0.002	0.998	0.018	0.003	0.003	0.001	0.975	0.405	0.007	0.010	0.002	0.576
3	0.001	0.001	0.000	0.014	0.984	0.030	0.002	0.000	0.013	0.955	0.000	0.000	0.000	0.002	0.998	0.018	0.004	0.003	0.002	0.973	0.405	0.007	0.010	0.002	0.576
4	0.001	0.001	0.000	0.014	0.984	0.030	0.002	0.000	0.013	0.955	0.000	0.000	0.000	0.002	0.998	0.018	0.004	0.003	0.002	0.973	0.405	0.007	0.010	0.002	0.576
5	0.001	0.001	0.000	0.014	0.984	0.030	0.002	0.000	0.013	0.955	0.000	0.000	0.000	0.002	0.998	0.018	0.004	0.003	0.002	0.973	0.405	0.007	0.010	0.002	0.576
6	0.001	0.001	0.000	0.014	0.984	0.030	0.002	0.000	0.013	0.955	0.000	0.000	0.000	0.002	0.998	0.018	0.004	0.003	0.002	0.973	0.405	0.007	0.010	0.002	0.576
7	0.001	0.001	0.000	0.014	0.984	0.030	0.002	0.000	0.013	0.955	0.000	0.000	0.000	0.002	0.998	0.018	0.004	0.003	0.002	0.973	0.405	0.007	0.010	0.002	0.576
8	0.001	0.001	0.000	0.014	0.984	0.030	0.002	0.000	0.013	0.955	0.000	0.000	0.000	0.002	0.998	0.018	0.004	0.003	0.002	0.973	0.405	0.007	0.010	0.002	0.576

MATIC	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.007	0.000	0.000	0.000	0.993	0.000	0.000	0.000	0.000	1.000	0.429	0.002	0.002	0.000	0.567	0.332	0.000	0.000	0.082	0.586
2	0.000	0.005	0.054	0.059	0.882	0.007	0.003	0.000	0.006	0.984	0.001	0.003	0.000	0.008	0.988	0.421	0.003	0.005	0.015	0.556	0.308	0.000	0.006	0.122	0.564
3	0.000	0.006	0.063	0.059	0.872	0.007	0.004	0.000	0.007	0.982	0.002	0.003	0.000	0.009	0.986	0.420	0.003	0.006	0.015	0.556	0.306	0.000	0.007	0.127	0.560
4	0.000	0.006	0.063	0.059	0.872	0.007	0.004	0.000	0.007	0.982	0.002	0.003	0.000	0.009	0.986	0.420	0.003	0.006	0.015	0.556	0.305	0.000	0.007	0.127	0.561
5	0.000	0.006	0.064	0.059	0.871	0.007	0.004	0.000	0.007	0.982	0.002	0.003	0.000	0.009	0.986	0.420	0.003	0.006	0.015	0.556	0.305	0.000	0.007	0.127	0.561
6	0.000	0.006	0.064	0.059	0.871	0.007	0.004	0.000	0.007	0.982	0.002	0.003	0.000	0.009	0.986	0.420	0.003	0.006	0.015	0.556	0.305	0.000	0.007	0.127	0.561
7	0.000	0.006	0.064	0.059	0.871	0.007	0.004	0.000	0.007	0.982	0.002	0.003	0.000	0.009	0.986	0.420	0.003	0.006	0.015	0.556	0.305	0.000	0.007	0.127	0.561
8	0.000	0.006	0.064	0.059	0.871	0.007	0.004	0.000	0.007	0.982	0.002	0.003	0.000	0.009	0.986	0.420	0.003	0.006	0.015	0.556	0.305	0.000	0.007	0.127	0.561

OP	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.110	0.000	0.000	0.000	0.890	0.419	0.025	0.000	0.000	0.556	0.101	0.017	0.160	0.000	0.722	0.065	0.010	0.101	0.161	0.663
2	0.001	0.001	0.026	0.019	0.953	0.107	0.010	0.010	0.000	0.873	0.417	0.029	0.002	0.000	0.552	0.102	0.019	0.158	0.008	0.713	0.063	0.016	0.099	0.158	0.664
3	0.001	0.001	0.027	0.019	0.952	0.108	0.010	0.010	0.000	0.872	0.416	0.029	0.002	0.001	0.552	0.102	0.019	0.158	0.008	0.713	0.063	0.016	0.099	0.158	0.664
4	0.001	0.001	0.027	0.019	0.952	0.108	0.010	0.010	0.000	0.872	0.416	0.029	0.002	0.001	0.552	0.102	0.019	0.158	0.008	0.713	0.063	0.016	0.099	0.158	0.664
5	0.001	0.001	0.027	0.019	0.952	0.108	0.010	0.010	0.000	0.872	0.416	0.029	0.002	0.001	0.552	0.102	0.019	0.158	0.008	0.713	0.063	0.016	0.099	0.158	0.664
6	0.001	0.001	0.027	0.019	0.952	0.108	0.010	0.010	0.000	0.872	0.416	0.029	0.002	0.001	0.552	0.102	0.019	0.158	0.008	0.713	0.063	0.016	0.099	0.158	0.664
7	0.001	0.001	0.027	0.019	0.952	0.108	0.010	0.010	0.000	0.872	0.416	0.029	0.002	0.001	0.552	0.102	0.019	0.158	0.008	0.713	0.063	0.016	0.099	0.158	0.664
8	0.001	0.001	0.027	0.019	0.952	0.108	0.010	0.010	0.000	0.872	0.416	0.029	0.002	0.001	0.552	0.102	0.019	0.158	0.008	0.713	0.063	0.016	0.099	0.158	0.664

FTM	CryptoMC					CryptoV					CryptoCS					CryptoTVL					BTCP				
	CryptoV	CryptoCS	CryptoTVL	BTCP	CryptoMC	CryptoMC	CryptoCS	CryptoTVL	BTCP	CryptoV	CryptoMC	CryptoV	CryptoTVL	BTCP	CryptoCS	CryptoMC	CryptoV	CryptoCS	BTCP	CryptoTVL	CryptoMC	CryptoV	CryptoCS	CryptoTVL	BTCP
Step	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd	fevd
0	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000
1	0.000	0.000	0.000	0.000	1.000	0.027	0.000	0.000	0.000	0.973	0.013	0.002	0.000	0.000	0.985	0.147	0.000	0.000	0.000	0.853	0.299	0.005	0.000	0.004	0.692
2	0.000	0.002	0.027	0.009	0.962	0.034	0.019	0.017	0.007	0.923	0.023	0.018	0.000	0.015	0.944	0.148	0.001	0.002	0.005	0.844	0.291	0.011	0.001	0.013	0.684
3	0.000	0.004	0.028	0.009	0.959	0.036	0.026	0.018	0.009	0.911	0.024	0.021	0.001	0.017	0.937	0.149	0.001	0.003	0.005	0.842	0.291	0.011	0.001	0.014	0.683
4	0.000	0.004	0.028	0.009	0.959	0.036	0.027	0.018	0.010	0.909	0.024	0.021	0.001	0.018	0.936	0.149	0.001	0.003	0.005	0.842	0.291	0.011	0.001	0.014	0.683
5	0.000	0.004	0.028	0.009	0.959	0.036	0.027	0.018	0.010	0.909	0.024	0.022	0.001	0.018	0.935	0.149	0.001	0.003	0.005	0.842	0.291	0.011	0.001	0.014	0.683
6	0.000	0.004	0.028	0.009	0.959	0.036	0.027	0.018	0.010	0.909	0.024	0.022	0.001	0.018	0.935	0.149	0.001	0.003	0.005	0.842	0.291	0.011	0.001	0.014	0.683
7	0.000	0.004	0.028	0.009	0.959	0.036	0.027	0.018	0.010	0.909	0.024	0.022	0.001	0.018	0.935	0.149	0.001	0.003	0.005	0.842	0.291	0.011	0.001	0.014	0.683
8	0.000	0.004	0.028	0.009	0.959	0.036	0.027	0.018	0.010	0.909	0.024	0.022	0.001	0.018	0.935	0.149	0.001	0.003	0.005	0.842	0.291	0.011	0.001	0.014	0.683