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Interconnectedness and Risk Structure Among Digital Assets: Empirical Findings Based on the Generalized R² Approach (2020–2025)

Dijital Varlıklar Arasındaki Bağlantılılık ve Risk Yapısı: Genelleştirilmiş R² Yaklaşımına Dayalı Ampirik Bulgular (2020–2025)

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ABSTRACT

This study analyzes the time-varying interactions among assets in the digital financial asset market. Within the scope of the study, 1,820 daily observations from the 2020-2025 period for Ethereum, Ripple, Binance Coin, Cardano, Stellar, IOTA, Stacks, and Chainlink are examined using the Generalized R² method proposed by Balli et al. (2023). This approach reveals both contemporaneous and lagged interconnectedness between assets, thereby enabling an understanding of how dynamic relationships evolve over time. The results indicate that market interconnectedness is not stable over time and that the transmission of shocks tends to intensify particularly during periods of uncertainty. The findings show that Ethereum maintained a central role throughout the analysis period, while Cardano, STX, LINK, and IOTA were more exposed to shocks. These results underscore the necessity of policy frameworks that address not only individual asset risks but also contagion risks to promote market stability. From an investor's perspective, it is recommended that portfolio compositions consider both contemporaneous and lagged effects.

Anahtar Kelimeler:
Dijital Finansal Varlıklar,
Kripto Varlıklar,
Bağlantılılık,
Risk,
Genelleştirilmiş R²
Jel Kodları:
C02, C30, C44

ÖZET

Bu çalışma, dijital finansal varlık piyasasındaki varlıklar arasındaki zamanla değişen etkileşimleri analiz etmektedir. Çalışma kapsamında, Ethereum, Ripple, Binance Coin, Cardano, Stellar, IOTA, Stacks ve Chainlink için 2020-2025 dönemine ait 1.820 günlük gözlem, Balli ve diğerleri (2023) tarafından önerilen Genelleştirilmiş R² yöntemi kullanılarak incelenmiştir. Bu yaklaşım, varlıklar arasındaki eşzamanlı ve gecikmeli karşılıklı bağlantıları ortaya çıkararak, dinamik ilişkilerin zaman içinde nasıl geliştiğini anlamayı mümkün kılmaktadır. Sonuçlar, piyasa karşılıklı bağlantısının zaman içinde istikrarlı olmadığını ve şokların iletilmesinin özellikle belirsizlik dönemlerinde yoğunlaşma eğiliminde olduğunu göstermektedir. Bulgular, Ethereum'un analiz dönemi boyunca merkezi bir rol sürdürdüğünü, Cardano, STX, LINK ve IOTA'nın ise şoklara daha fazla maruz kaldığını göstermektedir. Bu sonuçlar, piyasa istikrarını teşvik etmek için yalnızca bireysel varlık risklerini değil, aynı zamanda bulaşma risklerini de ele alan politika çerçevelerinin gerekliliğini vurgulamaktadır. Yatırımcıların bakış açısından, portföy bileşimlerinde hem eşzamanlı hem de gecikmeli etkilerin dikkate alınması önerilmektedir.

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1. INTRODUCTION

Digital asset markets have emerged as a prominent alternative to traditional financial instruments, offering innovative investment opportunities and decentralized financial engagement. Since Bitcoin's introduction in 2009, hundreds of digital assets—including high market-capitalization cryptocurrencies such as Ethereum, Binance Coin, Cardano, and Stellar—have been developed, rapidly gaining acceptance among investors (Wątorek et al., 2021; Fang et al., 2022; Corbet et al., 2019).

Key features of driving adoption include decentralization, limited supply, and 24/7 transaction capability, enabling investors to respond flexibly to market fluctuations, preserve capital, and reduce reliance on intermediaries (Bouri et al., 2017; Sutbayeva et al., 2024). These characteristics, combined with the market's rapid growth, underscore why digital assets have become a significant alternative investment class.

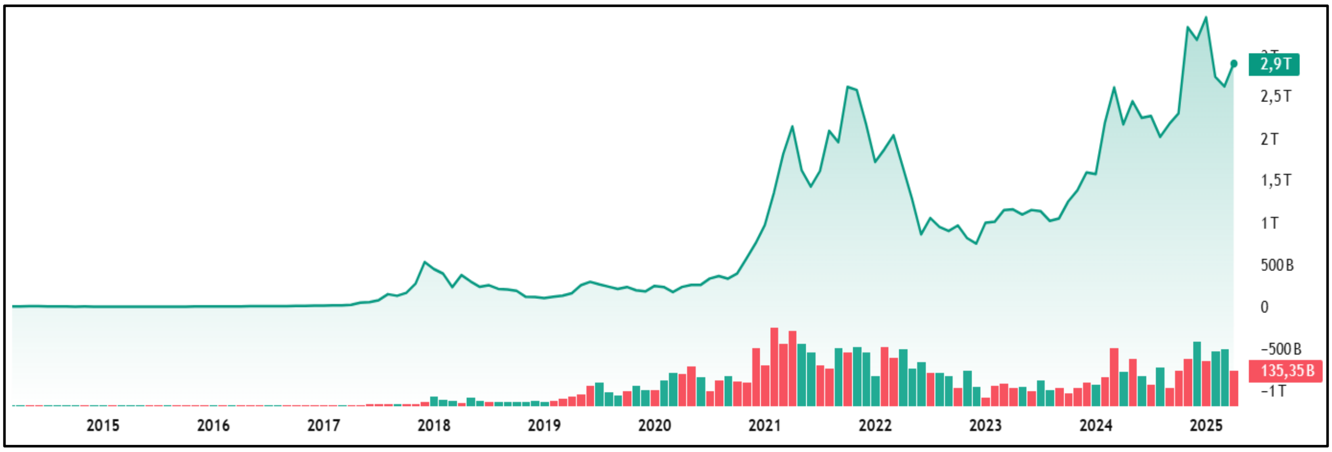

Figure 1. Total Monetary Volume of the Digital Asset Market (Trillion USD)

As shown in Figure 1, the digital asset market grew rapidly from 2020, declined sharply in 2022, and rebounded in 2023-2024, reaching around $3 trillion by 2025. This trend reflects growing investor demand and highlights the need to understand inter-asset interactions and systemic risk propagation.

Despite these advantages, digital assets carry significant risks, including high volatility, regulatory gaps, and limited transparency. Such factors can amplify systemic shocks, making it crucial to examine inter-asset relationships and investor behavior to develop effective risk management strategies (Ji et al., 2019; Umar et al., 2021). Regulatory frameworks such as the EU's Markets in Crypto-Assets (MiCA) regulation, the US Securities and Exchange Commission (SEC) oversight, and cryptocurrency guidelines in Japan and Singapore aim to mitigate systemic risks, enhance market transparency, and provide a structured environment for investors. Unlike traditional financial markets, digital assets are influenced by both macroeconomic conditions and micro-level drivers such as technological innovations, regulatory changes, and exchange-level interventions, resulting in time-varying interconnectedness that standard methods may not fully capture (Balli et al., 2023; Diebold & Yılmaz, 2014).

To address these challenges, this study employs the Generalized R^2 method on daily data from April 13, 2020, to April 7, 2025, covering eight major digital assets: cryptocurrencies (ETH, XRP, BNB), sustainable tokens (ADA, XLM, IOTA), NFTs (STX), and DeFi assets (LINK). By separating contemporaneous and lagged effects, the method identifies influential and influenced assets, tracks shock propagation, and highlights periods of heightened market interconnectedness.

This research contributes to literature by extending connectedness analysis to a broad set of digital assets within a unified framework, offering insights into contagion dynamics and systemic risk. From a policy perspective, understanding how interconnectedness evolves during crisis periods can support regulators in developing targeted interventions and assist investors in constructing resilient portfolios.

The remainder of the paper is structured as follows. The Introduction presents the background and objectives. The Literature Review synthesizes prior research and identifies the gap. The Data Set and Methodology section details the dataset, variables, and econometric approach. The Analysis Results section reports empirical findings on contemporaneous and lagged connectedness patterns. Finally, the Conclusion and Evaluation summarize key results, implications, and future research directions.

2. LITERATURE REVIEW

A review of the finance literature reveals that thousands of studies have been conducted on digital asset markets in recent years. The shift in investor preferences from traditional investment vehicles to digital assets has redirected scholarly attention toward this emerging field. Cheah & Fry (2015) examined speculative movements in Bitcoin prices, showing that market prices are often driven by irrational behaviors. Kristoufek (2015) highlighted the influence of social media on cryptocurrency markets, while Urquhart (2016) analyzed Bitcoin's market efficiency and concluded that it became increasingly rational over time. Katsiampa (2017) identified Bitcoin's volatility as highly sensitive to news and market interventions. Similarly, Conrad et al. (2018) observed a clustering tendency in Bitcoin's volatility, and Baur et al. (2018) emphasized the asset's inherently volatile and risky nature. Corbet et al. (2018) further investigated the bubble-like behaviors of Bitcoin and Ethereum, underlining their speculative characteristics. Expanding on this, Beneki et al. (2019) documented significant interdependence and intense volatility spillovers among cryptocurrencies. Ji et al. (2019) demonstrated that Bitcoin functions as a critical information transmitter within cryptocurrency markets, while Shahzad et al. (2020) confirmed that volatility spillovers primarily flow from Bitcoin to other altcoins. More recently, Bouri et al. (2021) and Umar et al. (2021) emphasized the vulnerability of cryptocurrency markets to external shocks, noting their exposure to both the COVID-19 pandemic and broader economic crises.

In parallel, a substantial body of research has explored dynamic connectedness and spillover mechanisms across financial, commodity, and digital asset markets. Akkus & Doğan (2024) examine the time-varying linkages among cryptocurrencies, NFTs, and DeFi assets using a TVP-VAR approach, demonstrating that digital markets are highly interconnected and prone to evolving risk transmission. Complementarily, Doğan et al. (2023) investigate the connectedness among clean energy markets, carbon emission allowances, and stock indices, highlighting the intensification of interlinkages during uncertain periods. Beyond digital markets, Balcı (2024) provides evidence of volatility spillovers among global stock markets during crisis episodes through a Diagonal BEKK framework, while Balcı (2025) analyzes the dynamic linkages between the Turkish Islamic stock market and global macroeconomic risk factors using a DCC-GARCH approach, both showing that systemic risks tend to strengthen in times of turbulence. Kyriazis & Corbet (2024) extend this line of research by evaluating the dynamic connectedness of financial assets and banking indices during black-swan events with a Quantile-VAR approach, finding that extreme events amplify systemic interconnectedness. Similarly, Li et al. (2024) assess connectedness between Chinese commodity and stock markets through TVP-VAR and cDCC-FIAPARCH models, emphasizing the role of hedging opportunities under time-varying dynamics.

Emerging research has also incorporated digital finance and FinTech perspectives. Yadav et al. (2025) investigate the time-varying interconnectedness among FinTech, digital assets, and electronic commerce, providing new insights into how technological innovation influences financial linkages. Likewise, Sharma et al. (2024) focus on the connectedness between commodities and ESG stocks in India, offering implications for sustainable investment strategies. Collectively, these studies confirm that financial and digital asset markets exhibit strong dynamic interdependencies, which tend to escalate during periods of stress or structural change.

Despite these advances, the existing literature has largely concentrated either on traditional financial markets, sector-specific indices, or limited segments of the digital asset ecosystem. Few studies have systematically examined the interconnectedness among a broad set of digital financial assets while considering both contemporaneous and lagged effects in a unified framework. Addressing this gap, the present study applies the Generalized R^2 method proposed by Balli et al. (2023) to analyze Ethereum, Ripple, Binance Coin, Cardano, Stellar, IOTA, Stacks, and Chainlink. By capturing time-varying relationships across multiple layers of interaction, this study contributes to a deeper understanding of contagion risk and stability implications in digital financial markets.

3. DATA SET and METHODOLOGY

3.1. Data Description

To examine the contagion dynamics in the digital asset market, the study uses daily price series of selected digital assets. Specifically, daily data from April 13, 2020, to April 7, 2025, are utilized to analyze interactions among eight leading digital assets: Ethereum (ETH), Ripple (XRP), Binance Coin (BNB), Cardano (ADA), Stellar (XLM), IOTA, Stacks (STXK) representing NFTs, and Chainlink (LINK) representing DeFi assets. The data for these variables were obtained from the Investing.com platform.

3.2. Methodology

In this study, the Generalized R^2 method is employed to examine the interactions among digital assets. The methodological framework and estimation steps of the approach are outlined as follows (Balli et al., 2023; Diebold & Yılmaz, 2012; Diebold & Yılmaz, 2014):

$$y_t = \sum_{i=1}^{p} B_i y_{t-i} + u_t \; and \; u_t \sim N(0, \Sigma) \tag{1}$$

Here, y_t t denotes the vector of log-returns of the interconnected indices at time. The coefficient matrix B_i reflects sectoral interconnectedness across different time periods, capturing the impact of each index on the others. The term u_t represents the error term.

Descriptive statistics for the digital assets included in the analysis are presented in Table 1. According to the figures reported in Table 1, the return series exhibit significant levels of skewness and kurtosis. Notably, STXK stands out with a skewness value of 7.854 and a kurtosis value of 102.46, indicating a highly speculative structure. Results from the Jarque-Bera test reveal that none of the series follow a normal distribution ($p < 0.01$). Moreover, the Q(10) and $Q^2(10)$ test statistics indicate the presence of statistically significant autocorrelation and ARCH effects in all series.

Table 1. Summary Statistics

	ETH	**XRP**	**BNB**	**ADA**	**XLM**	**IOTA**	**STXK**	**LINK**
Mean	2.924	3.368	2.777	3.621	3.358	3.819	4.58	4.039
Variance	8.947	22.223	13.086	16.538	20.887	16.26	29.208	15.07
Skewness	2.385***	5.411***	6.062***	4.540***	6.588***	3.317***	7.854***	2.431***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	9.563***	49.438***	77.921***	50.367***	74.278***	19.668***	132.840***	10.354***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	8655.189***	194118.592***	471318.556***	198520.412***	431315.145***	32655.306***	1356156.257***	9916.079***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-12.772***	-9.877***	-6.494***	-7.385***	-9.150***	-8.005***	-9.031***	-12.632***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	218.078***	370.897***	649.977***	257.387***	312.339***	256.228***	86.100***	281.917***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(10)$	150.243***	36.629***	165.184***	35.274***	38.751***	132.563***	2.494	233.442***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.886)	(0.000)

Note: Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit root test; Q(10) and $Q^2(10)$: Weighted Portmanteau test statistics proposed by Fisher and Gallagher (2012). P-values are reported in parentheses. Significance levels: * statistically significant at the 10% level, ** at the 5% level, and *** at the 1% level.

In the study, the calculation of total connectedness (TCI) and directional connectedness among assets is performed using Equation (2) (Diebold & Yılmaz, 2012; Diebold & Yılmaz, 2014):

$$TCI = \frac{1}{K} \sum_{k=1}^{K} R_k^2 \tag{2}$$

Using the Generalized R^2 decomposition, contemporaneous and lagged interactions are calculated as shown below using Equation (3) (Baur & Hoang, 2021):

$$R_{xx} = V \Lambda V' = CC' \tag{3}$$

4. ANALYSIS RESULTS

The findings regarding the levels of connectedness obtained using the Generalized R^2 method are presented below. The results indicate that information transmission in digital asset markets exhibits a directional, dynamic, and time-varying structure among assets.

Figure 2 illustrates the return series of the digital assets throughout the study period. An examination of Figure 2 reveals that fluctuations in returns occurred across all assets over time, and that similar return patterns emerged during several periods.

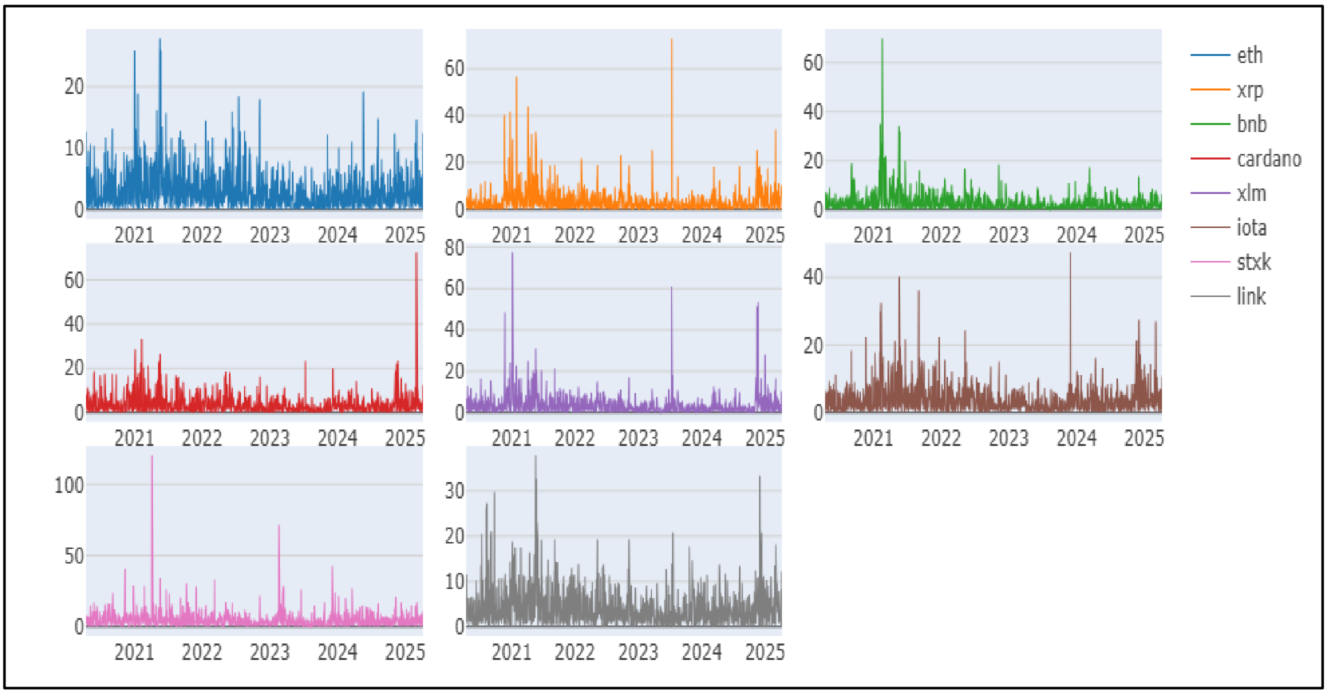

Figure 2. Logarithmic Return Series of Digital Assets

According to the dynamic total connectedness results presented in Figure 3, the Total Connectedness Index (TCI) exhibits a fluctuating pattern over time, with occasional surges above the 50% level, indicating periods of intensified systemic risk. These increases are particularly evident during periods characterized by external shocks. This finding suggests that systemic vulnerability intensifies at certain times, and information transmission triggers a chain reaction across the market.

The figure reveals that the overall connectedness level experienced substantial volatility over the years, peaking at the end of 2022. This result indicates heightened interdependence among assets during that period and a stronger propagation of market shocks. The contemporaneous connectedness level also follows a similarly volatile trend over the years, closely mirroring the behavior of overall connectedness. In contrast, the lagged connectedness level generally displays a lower and more stable pattern.

These findings collectively suggest that shock transmission within the digital asset market intensifies particularly during periods of uncertainty and crises. Moreover, lagged effects appear to exhibit a more dominant structure compared to contemporaneous effects.

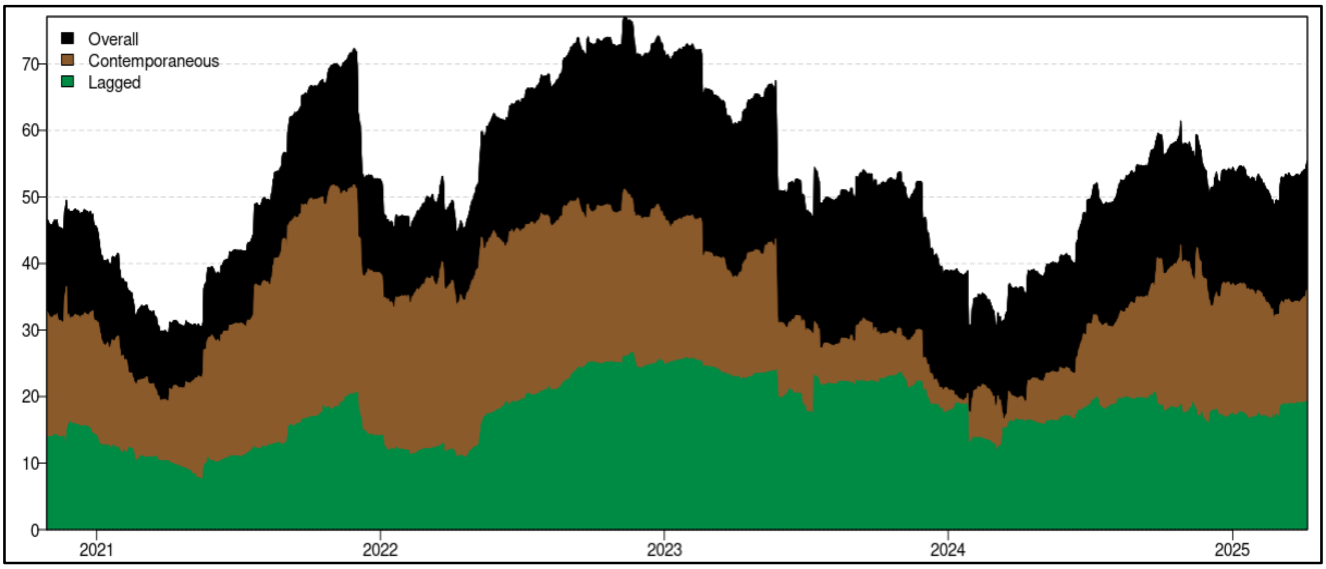

Figure 3. Dynamic Total Connectedness

According to the net total connectedness results presented in Figure 4, Ethereum (ETH) emerges as the most prominent shock transmitter in the market. Notably, there has been a significant increase in TDC values in the most recent periods, indicating that ETH has strengthened its leadership role and systemic impact within the market. Meanwhile, assets such as Cardano (ADA), Chainlink (LINK), and IOTA have exhibited relatively balanced and low levels of connectedness throughout the analysis period, suggesting that they have predominantly acted as shock receivers.

On the other hand, assets like Binance Coin (BNB), Ripple (XRP), and Stellar (XLM) have displayed notable fluctuations over time. BNB, for instance, has alternated between acting as a shock transmitter and a shock receiver across different periods. XRP transitioned into a shock transmitter position toward the end of 2024, while XLM increased its influence on the market following 2022 but subsequently lost this impact. Overall, the results confirm that the structure of interconnectedness among digital assets is dynamic and undergoes significant changes over time.

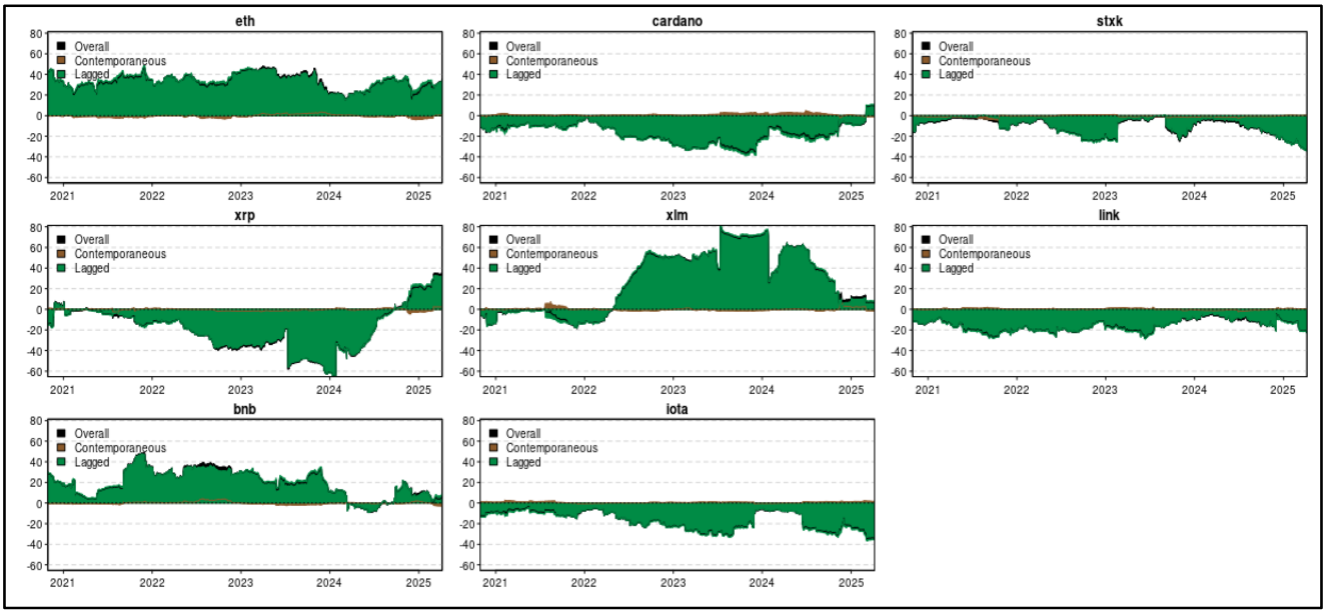

Figure 4. Net Total Directional Connectedness (TDC)

In this study, the interactions among the digital assets included in the analysis are measured through connectedness matrices, which express the impact of a shock occurring in one asset on the others. Table 2 below presents the results of the overall connectedness matrix. According to the results reported in Table 2: Ethereum (ETH) (75.34), Stellar (XLM) (72.77), and Binance Coin (BNB) (60.1) exhibit the highest total impact scores, indicating that these assets exert the strongest influence over the others. Moreover, their positive net impact scores reveal that they predominantly act as shock transmitters within the system. On the other hand, assets such as Cardano (ADA), IOTA, Stacks (STXK), and Chainlink (LINK) are identified as net shock receivers in the system.

Table 2. Overall Connectedness Matrix

FROM	Overall ETH	Overall XRP	Overall BNB	Overall ADA	Overall XLM	Overall IOTA	Overall STXK	Overall LINK	Overall FROM
ETH	0,71	1,91	23,99	1,32	10,64	1,13	0,87	1,97	41,84
XRP	5,67	2,08	4,24	8,8	26,05	5,4	3,39	4,62	58,16
BNB	23,87	2,22	2,61	1,82	7,07	1,88	1,05	2,75	40,66
ADA	8,34	8,51	5,86	1,31	12,49	7,17	3,79	8,98	55,13
XLM	12,09	11,9	7,83	5,56	1,47	2,52	2,05	3,56	45,51
IOTA	7,98	6,32	6,27	7,37	6,61	0,71	4,71	7,94	47,2
STXK	5,69	3,46	5	4,14	3,65	4,53	1,37	3,88	30,36
LINK	11,7	4,81	6,9	8,92	6,27	7,59	3,49	0,59	49,67
TO	75,34	39,13	60,1	37,94	72,77	30,22	19,34	33,7	368,53
Inc.Own	76,05	41,21	62,7	39,25	74,23	30,93	20,71	34,29	cTCI/TCI
NET	33,51	-19,02	19,44	-17,19	27,25	-16,98	-11,02	-15,98	52.65/46.07

When examining the results of the contemporaneous connectedness matrix presented in Table 3: XLM (37.85), ETH (37.33), and BNB (33.87) exhibit the highest contemporaneous impact scores on other assets. These assets possess strong instantaneous influence over others, whereas STXK (15.99), IOTA (26.7), and LINK (28.16) display a more limited contemporaneous impact. An analysis of the net impact scores indicates that all assets are engaged in relatively similar levels of interaction, suggesting a generally homogeneous structure across the system.

Table 3. Contemporaneous Connectedness Matrix

FROM	C⁺ ETH	C* XRP	C* BNB	C* ADA	C* XLM	C* IOTA	C* STXK	C* LINK	C* FROM
ETH	0	1,39	23,31	0,83	9,94	0,66	0,57	1,12	37,82
XRP	1,25	0	0,8	7,81	10,25	5,02	2,78	3,99	31,91
BNB	23,12	0,84	0	0,86	5,86	1,1	0,65	1,49	33,94
ADA	0,74	7,55	0,77	0	4,98	6,66	3,35	8,19	32,25
XLM	10,05	10,08	5,96	5	0	2,06	1,76	2,95	37,87
IOTA	0,56	4,89	0,98	6,67	2,01	0	3,75	7,21	26,07
STXK	0,59	2,96	0,66	3,57	1,9	3,9	0	3,21	16,79
LINK	1	3,83	1,38	8,43	2,91	7,3	3,12	0	27,98
TO	37,33	31,54	33,87	33,18	37,85	26,7	15,99	28,16	244,62
Inc.Own	37,33	31,54	33,87	33,18	37,85	26,7	15,99	28,16	cTCI/TCI
NET	-0,48	-0,37	-0,07	0,93	-0,02	0,63	-0,8	0,18	34.95/30.58

Note: Contemporaneous

When examining the results of the lagged connectedness matrix presented in Table 4: The assets with the highest lagged effects are ETH (38.01), XLM (34.91), and BNB (26.22). These results suggest that ETH, XLM, and BNB serve as the primary actors in the medium- and long-term transmission of information within the system. Moreover, their positive net values indicate that they also act as shock transmitters in lagged interactions. In particular, Ethereum's net value (33.99) and XLM's net value (27.27) demonstrate that these assets have a strong and lasting influence over the system. On the other hand, XRP (-18.66), ADA (-18.22), and LINK (-16.16) exhibit negative net scores, identifying them as net shock receivers. These findings imply that for some assets, shock effects do not diminish over time but instead continue to propagate throughout the system in a lagged manner.

Table 4. Lagged Connectedness Matrix

FROM	Lagged ETH	Lagged XRP	Lagged BNB	Lagged ADA	Lagged XLM	Lagged IOTA	Lagged STXK	Lagged LINK	Lagged FROM
ETH	0,71	0,53	0,68	0,49	0,7	0,47	0,31	0,85	4,02
XRP	4,41	2,08	3,43	0,99	15,79	0,39	0,6	0,63	26,25
BNB	0,75	1,38	2,61	0,95	1,2	0,77	0,4	1,26	6,71
ADA	7,6	0,96	5,09	1,31	7,51	0,51	0,44	0,79	22,89
XLM	2,03	1,82	1,87	0,57	1,47	0,46	0,29	0,61	7,65
IOTA	7,42	1,44	5,3	0,7	4,6	0,71	0,95	0,73	21,13
STXK	5,1	0,5	4,34	0,57	1,76	0,63	1,37	0,67	13,58
LINK	10,69	0,98	5,52	0,49	3,36	0,29	0,36	0,59	21,7
TO	38,01	7,59	26,22	4,76	34,91	3,52	3,35	5,54	123,91
Inc.Own	38,72	9,67	28,83	6,08	36,38	4,23	4,72	6,13	cTCI/TCI
NET	33,99	-18,66	19,51	-18,12	27,27	-17,61	-10,22	-16,16	17.70/15.49

The total influence of the assets on other assets, as presented in Tables 2, 3, and 4, is illustrated in Figure 5. The data in Figure 5 reveal that Ethereum (ETH) and Binance Coin (BNB) acted as strong shock transmitters particularly during the 2021-2022 period, while Stellar (XLM) assumed a dominant role during 2023-2024. Additionally, Ripple (XRP) has emerged as a prominent shock transmitter in the most recent period.

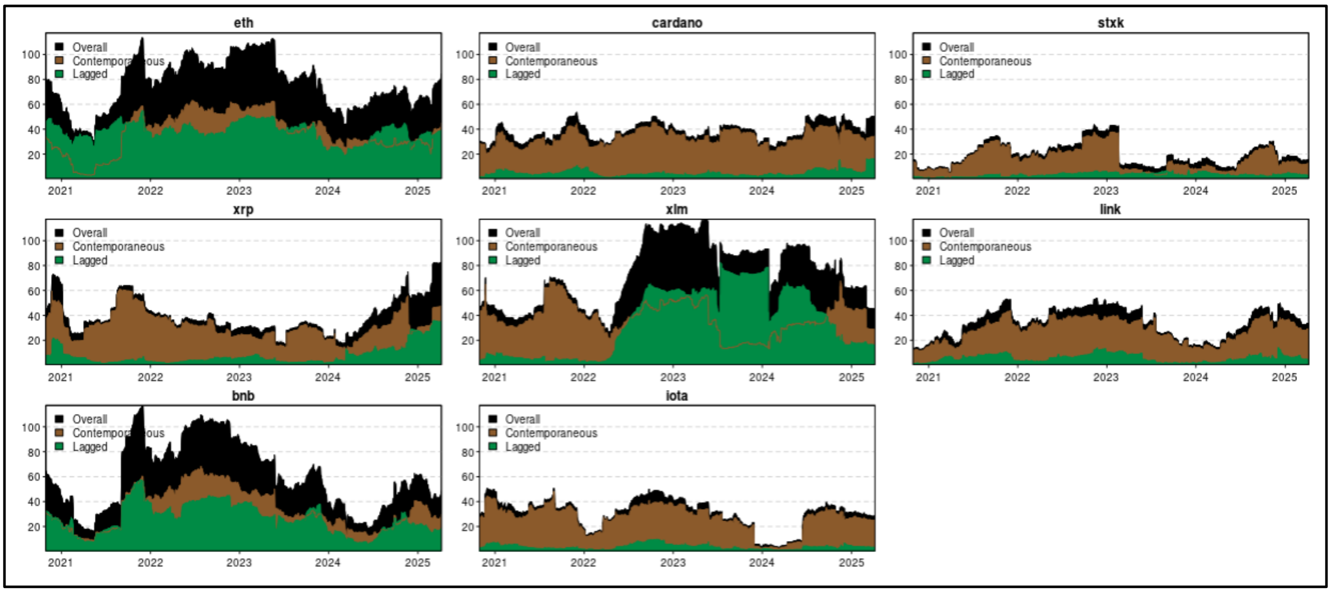

Figure 5. Total Impact on Others

According to the information presented in Figure 6, which illustrates the total shock received by each asset from others (as derived from Tables 2, 3, and 4), the results indicate that assets exhibit varying degrees of shock sensitivity over time. In particular, XRP, ADA, and IOTA appear to have been significantly affected during the post-2023 period. These findings demonstrate that the roles of shock reception and transmission fluctuate over time, highlighting the importance of dynamic analyses in understanding the interactions among digital assets.

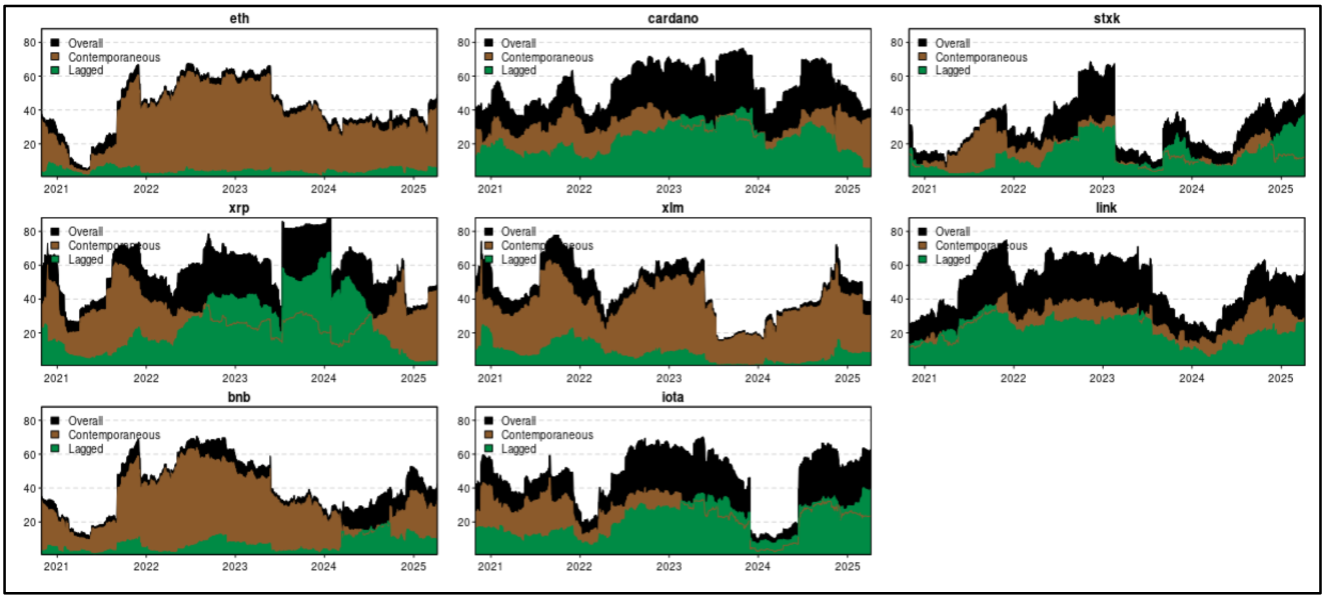

Figure 6. Total Impact from Others

Figure 7 presents the network of connectedness among the digital assets. The visuals in Figure 7 sequentially display contemporaneous, lagged, and overall connectedness relationships. According to the information presented in the figure 7:

Contemporaneous Connectedness: IOTA and ADA exhibit a strong contemporaneous linkage. The connection between these financial assets is relatively high, meaning that their price movements tend to influence each other simultaneously. This suggests that both assets are likely affected by similar underlying factors.

Lagged Connectedness: XRP, LINK, and STXK demonstrate stronger lagged relationships compared to other assets. This implies that these assets tend to react more slowly to market price movements, reflecting delayed responses to shocks.

Overall Connectedness: ADA and IOTA are identified as the most interconnected assets in the market, exhibiting the highest levels of total interaction.

A general assessment of Figure 7 reveals that the nature of connectedness among assets varies between contemporaneous and lagged effects. While the contemporaneous network appears relatively sparse, the lagged network demonstrates denser and more complex interrelationships.

Notably, Ethereum occupies a central position across all three graphs, exerting both immediate and persistent influence over other assets.

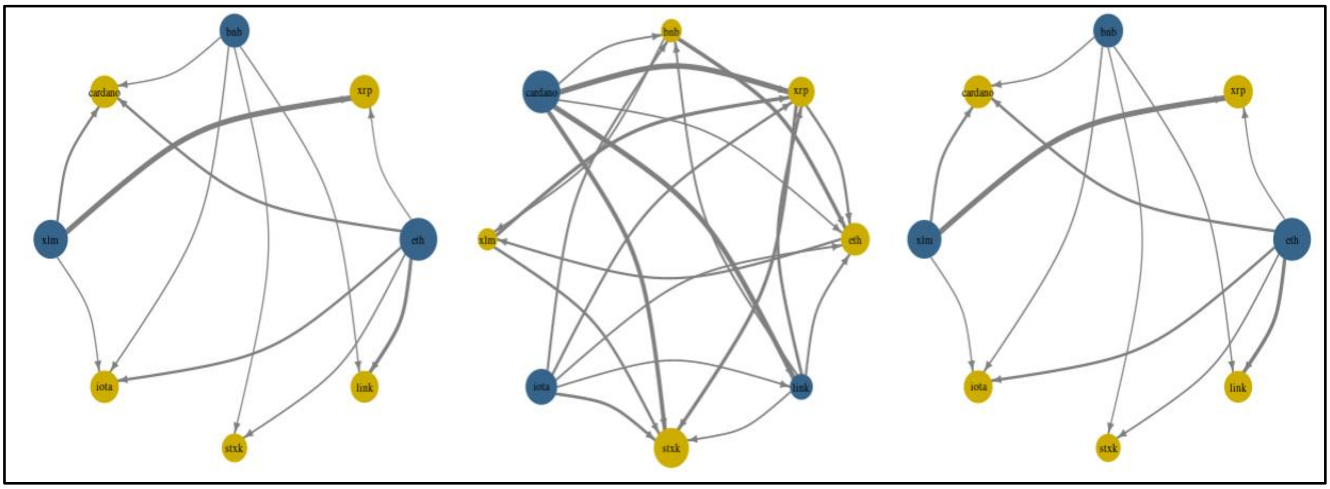

Figure 7. Volatility Spillover Network Graph

5. CONCLUSION and EVALUATION

The findings indicate that the level of interconnectedness in the digital asset market varies significantly over time and intensifies during periods of financial distress. This outcome necessitates the attention not only of individual investors but also of market regulators and policymakers due to the potential for contagion effects across financial markets. From a policy perspective, understanding how interconnectedness evolves during crisis periods can support regulators in developing targeted interventions. These insights can inform ongoing regulatory initiatives, such as the EU MiCA framework, US SEC enforcement policies, and Asian cryptocurrency regulations in Japan and Singapore, to strengthen market stability and manage contagion risks (Balli et al., 2023; Akkus & Doğan, 2024). Accurately analyzing contemporaneous and lagged connectedness effects is essential for designing risk-focused policies that support market resilience.

For investors engaged in portfolio diversification, it is crucial to make decisions not only based on returns but also by considering the interconnectedness characteristics of assets during crisis periods. Taking precautionary measures during periods of heightened volatility can help construct more resilient investment strategies (Ji et al., 2019; Yousaf & Yarovaya, 2022).

When compared with existing literature, the results of this study are broadly consistent with prior evidence emphasizing the time-varying and crisis-sensitive nature of connectedness. For instance, Ji et al. (2019) demonstrated that cryptocurrency markets exhibit strong dynamic integration, particularly during turbulent periods, which aligns with the present study’s finding that shocks intensify contagion across digital assets in times of financial distress. Similarly, Li et al. (2023) showed that cryptocurrencies and traditional financial assets in China are subject to time- and frequency-dependent connectedness, underscoring the importance of analyzing both short- and long-term spillovers—an approach also captured by the use of the Generalized R^2 method in this research.

In a related strand of literature, Yousaf & Yarovaya (2022) highlighted significant interconnectedness between NFTs, DeFi, and other assets, with implications for portfolio construction. This complements the current study’s results, as both analyses stress that diversification strategies must account for cross-asset contagion rather than relying solely on return correlations. On the other hand, Gong & Xu (2022), focusing on commodity markets under geopolitical risks, found that external shocks can substantially reshape interconnectedness patterns. Although the asset classes differ, this comparison reinforces the broader conclusion that systemic shocks—whether geopolitical or financial—amplify market interdependence.

Taken together, these comparisons show that while prior studies have primarily examined either specific asset classes or particular risk channels, the present research adds value by integrating multiple types of digital assets (cryptocurrencies, sustainable tokens, NFTs, and DeFi) into a unified framework that distinguishes between contemporaneous and lagged connectedness. This broader scope not only confirms the crisis-sensitivity of connectedness identified in earlier studies but also provides a more nuanced understanding of how shocks propagate through diverse segments of the digital asset ecosystem.

Future research could extend this framework by including additional digital assets, performing cross-country comparisons, or incorporating regulatory shocks to further investigate systemic risk dynamics and market resilience.

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The entire research is written by the author.

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