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Dynamic Volatility Propagation of Cryptocurrency Types [1]

Kripto Para Türlerinin Dinamik Volatilite Yayılımı

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Abstract
This study aims to analyze the volatility spillovers between Bitcoin and Ethereum, the two main actors in the cryptocurrency market, and altcoins across sectoral and financial groups. Using data from January 1, 2021, to March 6, 2023, the study applied the VAR-based method developed by Diebold and Yılmaz (2012) and measured both directional and total volatility spillovers. The findings show that Bitcoin's volatility largely stems from internal dynamics and spreads to other cryptocurrencies to a limited extent. In contrast, Ethereum is more affected by external shocks and exhibits a stronger volatility spillover across the market. Among altcoin categories, Gaming, Analytics, and DeFi groups were found to be the most influential in volatility transmission, while thematic tokens such as NFT, Web3, and Metaverse were more sensitive to external volatility. In contrast, stablecoins and tokens in the identity and healthcare sectors were found to have relatively low volatility and a more stable structure. These results offer important insights for investors and regulators regarding risk management strategies and portfolio diversification. The study provides a valuable framework for understanding the systematic volatility dynamics within the cryptocurrency ecosystem

Keywords: *Cryptocurrency, Volatility Spillover, Bitcoin, Ethereum, Altcoins, Diebold-Yılmaz Method.*

Jel Codes: *C32, C58, G15.*

Öz
Bu çalışma, kripto para piyasasının iki ana aktörü olan Bitcoin ve Ethereum ile altcoinlerin sektörel ve finansal grupları arasındaki volatilite yayılımlarını analiz etmeyi amaçlamaktadır. 1 Ocak 2021 – 6 Mart 2023 dönemi verileri kullanılarak gerçekleştirilen çalışmada, Diebold ve Yılmaz (2012) tarafından geliştirilen VAR temelli yöntem uygulanmış ve hem yönlü hem de toplam volatilite yayılımları ölçülmüştür. Bulgular, Bitcoin'in volatilitesinin büyük ölçüde iç dinamiklerden kaynaklandığını ve diğer kripto paralara sınırlı düzeyde bulaştığını göstermektedir. Buna karşın, Ethereum'un dışsal şoklardan daha fazla etkilendiği ve piyasa genelinde daha güçlü bir volatilite yayılımı sergilediği görülmüştür. Altcoin kategorileri arasında Oyun (Gaming), Analitik (Analytics) ve DeFi gruplarının volatilite aktarımında en etkili gruplar olduğu; NFT, Web3 ve Metaverse gibi tematik tokenlerin ise dışsal volatiliteye daha duyarlı olduğu belirlenmiştir. Buna karşılık, stablecoinler ve kimlik ile sağlık sektörlerindeki tokenlerin görece düşük volatiliteye ve daha istikrarlı bir yapıya sahip olduğu saptanmıştır. Bu sonuçlar, yatırımcılar ve düzenleyiciler açısından risk yönetimi stratejileri ile portföy çeşitlendirmesi konularında önemli çıkarımlar sunmaktadır. Çalışma, kripto para ekosistemi içerisindeki sistematik volatilite dinamiklerini anlamak için değerli bir çerçeve ortaya konulmuştur.

Anahtar Kelimeler: *Kripto Para Birimi, Volatilite Yayılımı, Bitcoin, Ethereum, Altcoinler, Diebold-Yılmaz Method.*

Jel Kodları: *C32, C58, G15.*

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1. INTRODUCTION

One of the most significant transformations in recent financial markets has been the emergence of cryptocurrency markets. Bitcoin, launched in 2009 by Satoshi Nakamoto in the article "Bitcoin: A Peer-to-Peer Electronic Cash System," marked the inception of digital currencies. Its primary purpose was to facilitate virtual money transfers without intermediaries, ensuring speed, low transaction costs, and enhanced security. Beyond these features, the blockchain technology underlying Bitcoin has been the pioneer of many innovations, such as the creation of many cryptocurrencies. Bitcoin and blockchain algorithms have been scrutinized, and even the slightest error has been resolved with rescue solutions within the algorithm. These algorithms contain high-level economic information and cannot be stolen by hackers. In addition, privacy is of utmost importance, and a high level of confidentiality is ensured. Since identification cannot be traced in trading transactions, the rate of use in illegal transactions has increased. After the positive atmosphere created by Bitcoin in the financial markets, Ethereum was introduced to the market in 2015. Ethereum, which is second only to Bitcoin in terms of market capitalization, has become a platform that enables the rapid development of smart contracts and decentralized applications in addition to being a cryptocurrency. Following the impact and development of both digital currencies in the financial markets, many new cryptocurrencies have emerged in the digital currency markets. As an alternative to Bitcoin and Ethereum, new cryptocurrencies have attracted the attention of investors with different infrastructures and usage purposes.

Although, initially regarded as unfamiliar, intangible, and high risk due to their volatility and lack of traditional recourse mechanisms, cryptocurrencies have been designed on the basis of years of technological progress and practical experience (Çakan, 2022: 21). The acceleration of digitalisation has diversified needs, catalysing the emergence of alternative forms of value transfer that are faster, more secure, and less dependent on traditional intermediaries. Blockchain technology, as an extension of these changes, has influenced financial markets by enabling transparent, rapid, and secure asset transfers on ledgers widely verifiable by network participants. Without the requirement for a central authority, on-chain records are designed to be tamper-evident, and all ledger information is stored in a system that is widely accessible (Gültekin and Bulut, 2016: 83).

Cryptocurrencies have also entered portfolios as investment instruments, largely due to pronounced price volatility (Baek & Elbeck, 2014: 30). The growth in transaction volumes, the diversity of crypto-assets, and the high variability of returns have attracted investors, regulators, and researchers alike. Bitcoin and Ethereum, in particular have played central roles in shaping market dynamics. While a new financing paradigm is envisioned in which these digital assets become increasingly integrated into daily life and markets, uncertainty remains for some investors regarding adoption and valuation. Nevertheless, the scale achieved by leading assets such as Bitcoin and Ethereum has positioned them as investable instruments in a growing number of contexts, as evidenced by recent financial reporting.

With the expansion of altcoins alongside Bitcoin and Ethereum, market participants are increasingly interested in identifying interactions and relationships across assets. Although Altcoins are strongly influenced by the market fundamentals of Bitcoin and Ethereum, the degree and direction of these relationships vary due to heterogeneous dynamics. Differences in investment focus, capitalisation, and sectoral orientation across Altcoins are therefore highly relevant for assessing volatility spillovers both from Bitcoin and Ethereum and within the broader Altcoin universe.

This study aims to shed light on the dynamics of the cryptocurrency market by analysing the volatility spillovers among Bitcoin, Ethereum, and altcoins, the two principal drivers and the broader market segments of the cryptocurrency ecosystem. Given the importance of volatility for investment decisions, the results of the study will provide informative evidence for investors and market observers.

2. LITERATURE REVIEW

Cryptocurrency Research on volatility, price dynamics, and market relationships in cryptocurrency markets has been increasing in recent years. These studies have been conducted to understand the effects of Bitcoin and Ethereum, which are the basic dynamics of the market, on the market and to identify the relationships between altcoins and these major cryptocurrencies, providing important information to investors, market actors, regulators, and researchers. The literature review on the subject will be presented under three headings: (1) Volatility Modelling and Spillovers; (2) Causality and Inter-Market Linkages; (3) Portfolio Diversification and Bubble Dynamics.

2.1. Volatility Modelling and Spillovers

Early concerns about the institutional and legal framing of crypto-assets emerged alongside the first major price fluctuations in Bitcoin. Analyzing the legal implications of Bitcoin's status after the October 2011 volatility episode, Grinberg (2011) argued that the technology's regulatory ambiguity entailed substantial risks for users and investors and could facilitate money laundering and tax evasion, thereby motivating the need for legal and supervisory frameworks. Methodologically, Diebold and Yilmaz (2012) introduced a vector autoregression-based connectedness framework that measures volatility spillovers via generalized forecast error variance decompositions, enabling order-invariant assessment of cross-market transmission, a tool later adapted to crypto-asset markets. In the context of Bitcoin's conditional variance dynamics, Katsiampa (2017) compared alternative GARCH-class models and showed that incorporating both short- and long-term components yields superior fit, identifying the AR-CGARCH specification as the most suitable for volatility estimation.

As market breadth expanded, research shifted towards multivariate volatility interactions across crypto-assets. Elendner et al. (2016) highlighted that Altcoins serve heterogeneous functions—including speculative trading and, at times, manipulation—while maintaining varying degrees of linkage to Bitcoin. Yi et al. (2018), examining 52 cryptocurrencies, documented time-varying volatility spillovers that intensify during turbulent periods and identified Bitcoin, Litecoin, and Name coin as net transmitters; Bitcoin, in particular, emerged as a key shock propagator. Broadening the scope to traditional markets, Iyer and Popescu (2023) applied the Diebold–Yilmaz connectedness approach to cryptocurrencies and conventional financial assets, showing that Bitcoin and Litecoin play material roles in volatility propagation and that cross-market connectedness strengthens during episodes of macroeconomic change. Complementing these findings, Antonakakis et al. (2019) reported that inter-cryptocurrency relationships generally strengthen in periods of heightened uncertainty, consistent with a regime-dependent spillover structure.

2.2. Causality and Inter-Market Linkages

Causality analyses have clarified the direction and strength of lead–lag dynamics within the crypto-asset ecosystem. Karaağaç and Altınırmak (2018) identified short-run causal effects between Bitcoin and various Altcoins, showing how selected Altcoins influence price changes in other cryptocurrencies. Extending this line of inquiry, Anyfantaki et al. (2018) considered portfolio implications of these interdependencies, while Nguyen et al. (2019) investigated determinants of Ethereum's price and found that Bitcoin, Litecoin, and Monero exert significant effects on Ethereum, suggesting a hierarchical influence structure among major coins. Using Granger causality and related time-series tools, Kayral (2020) and Aksoy et al. (2020) further mapped directional relationships, indicating which cryptocurrencies tend to drive others and thereby offering decision-relevant signals for market participants. Together, these studies suggest that causality patterns are non-symmetric, can shift across regimes, and frequently align with the broader volatility spillover networks documented in connectedness analyses.

2.3. Portfolio Diversification and Bubble Dynamics

The implications of crypto-assets for portfolio construction and market stability have been investigated across distinct risk regimes. Focusing on investor motives and competitive dynamics, Alpago (2018) underscored the importance of monitoring innovation and behavioral drivers in the crypto market. A series of studies reported diversification benefits from integrating cryptocurrencies into multi-asset portfolios: Anyfantaki et al. (2018) highlighted potential gains for risk-averse investors; Feng et al. (2018) emphasized distinctive features that can improve risk-adjusted outcomes; Ketelaars (2018) found improved performance with crypto allocations; and Wong et al. (2018) documented that certain cryptocurrencies can provide hedging or safe-haven properties under specific conditions. Hrytsiuk et al. (2019) noted Bitcoin's dominant role in diversified portfolios, an observation consistent with its centrality in spillover networks.

Exploring cross-asset co-movement, Corbet et al. (2020) examined Bitcoin, major Altcoins, and traditional assets (gold, oil, and the S&P 500), evidencing non-trivial interlinkages that vary over time and market states—information crucial for portfolio and risk management. In parallel, studies on speculative dynamics and bubble formation have grown. Halipli et al. (2020) associated high Bitcoin trading volumes with the emergence of bubbles and provided timing evidence around such episodes. Investigating bubble detection and investor behavior, Buğan (2021) discussed indicators and precautions relevant to bubble periods. Shu et al. (2021) differentiated endogenous versus exogenous drivers of Bitcoin's bubbles and crashes, suggesting that both internal market dynamics and external shocks can precipitate boom–bust cycles.

3. DATA AND METHODOLOGY

3.1. Data

The purpose of this study is to identify the volatility spread between Bitcoin and Ethereum, two main dynamics of the cryptocurrencies market and altcoins. In the scope of the study, altcoins other than Bitcoin and Ethereum are included in the analysis by indexing them by sectoral and financing areas. Thus, by indexing altcoin groups, a structure that will give an idea about the overall altcoins has been created. The sectoral and financial areas included in the analysis and the five altcoins with the highest trading volume used in the index calculation for these areas are presented in Table 1.

Table 1. Indices and Their Constituent Altcoins

Indices	**Altcoins**				
Analytics	Bird.Money	Dextools	Parsıq	The Graph	Viberate
Defi	Chainlink	Dai	Wrapped Bitcoin	Uniswap	Avalanche
Gaming	Render Token	Axie Infinity	Enjin Coin	Gala	The Sandbox
Health	Dentacoin	Doc.com	MediBloc	Medicalchain	Solve
Identity	Civic	Energy Web Token	Metadium	Ontology	Veruscoin
Iot Coin	DigiByte	Helium	Iota	Iotex	Vechain
Logistics	Morpheus.Network	Vechain	Wabi	Waltonchain	XYO
Marketing	Adshares	Ambire Adex	Basic Attention Token	Sether	Wabi
Memes Coin	Dogecoin	Banano	Monacoin	Shiba Inu	Erc 20
Metaverse	Axie Infinity	Decentraland	Enjin Coin	Theta Network	The Sandbox
Music	Audius	Ceek Vr	Forj(Bondly)	Viberate	Measurable Date
Privacy	Dash	Decred	Oasis Network	Monero	Zcash
Stablecoin	Binance	Dai	Frax	Tether	Usd Coin
Stroge	Arweave	Filecoin	Holo	Siacoin	Anrk
Tourism	Evencoin	Travala	LockTrip	XcelToken Plus	Kemacoin
Wallet	Voyager Token	Circuits of Value	Loopring	1inch Network	Trust Wallet Token
Web3	Chainlink	Filecoin	Stacks	Polkadot	Theta Network
NFT	Render Token	Axie Infinity	Tezos	Conflux	The Sandbox

Formula (1) was used to calculate the indices used in the study and formula (2) was used to calculate the returns of the cryptocurrencies used in the analysis.

$$\sum_{i=1}^{5}\left(\frac{MV_i}{TMV_i}\right) \text{x } CV_i \quad (1)$$

MV: Altcoin market capitalization,

TMV: Sum of the market capitalizations of all coins in the altcoin group,

CV: Altcoin closing price.

$$\frac{CP_t - CP_{t-1}}{CP_{t-1}} \tag{2}$$

CP_t: Closing price on day.

CP_{t-1}: Closing price of the previous day.

The analysis covers January 1, 2021 and March 6, 2023. All cryptocurrency data were obtained from the CoinGecko website, and the econometric analysis was conducted using the EViews 12.0 software.

3.2. Methodology

For the analysis of volatility spillovers between variables, the methodology developed by Diebold and Yilmaz (2012) based on the VAR model will be used. The reason for choosing the Diebold and Yilmaz (2012) methodology is that econometric methods developed for the detection of volatility spillovers can indicate the source of volatility spillovers across markets. This methodology simultaneously shows the volatility dispersion across markets and the change in volatility over time through a contagion table and allows for the analysis of periods of financial stress. The Diebold and Yilmaz (2012) methodology can be used to identify the cycles of return and return volatility dispersion in asset markets across markets (Karabıyık, 2020: 272). The methodology was used to measure the spillovers and overcome the shortcomings of the previous methodology (Yağcılar, 2021: 947). The N-variable covariance VAR(p) model is given below in Equation 3 (Gemici, 2020: 3145).

$$X_t = \sum_{t=1}^{p} \theta_i X_{t-i} + \varepsilon_t \tag{3}$$

The error vector is denoted by ε~(0, Σ), which is independent of each other and has the same distribution (Karabıyık 2020: 272). Equation (4) shows the moving average representation of the VAR model. The moving average representation is of great importance for understanding the system's dynamics it allows the variance decomposition to be calculated (Gemici, 2020: 3145).

$$X_t = \sum_{t=1}^{\infty} A_i \varepsilon_{t-i} \tag{4}$$

In Equation (2), A_0NxN is a unit matrix and Ai is represented by NxN coefficient matrix. When i<0, Ai=0 (Karabıyık 2020: 272). Furthermore, Equation (4) expresses an NxN coefficient matrix satisfying the recursion condition Ai=Φ1Ai-1+Φ2Ai-2+⋯. +ΦpAi-p (Yağcılar 2021: 947).

The Diebold and Yilmaz (2012) methodology uses the generalized VAR framework first developed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) (KPPS) to perform variance decompositions without changing the ordering of variables in the VAR system. The KPPS forecast error variance decomposition (H step forward) is calculated as shown in Equation (5) (Gemici, 2020: 3145).

$$\theta_{ij}^{g}(H) = \sigma_{ii}^{-1} \frac{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma A_i' e_h\right)} \tag{5}$$

Σ in Equation 5 denotes the estimated variance matrix of the error vector (ε). σij denotes the standard deviation of the error terms in the i. equation, the standard deviation of the j. error term and ei denotes the value one or zero in the selection vector (Karabıyık 2020: 272). In the calculation of the diffusion index, using the information in the variance decomposition matrix, each entry of the variance decomposition matrix is normalized by the row sum as in equation (6).

$$\sum_{j=1}^{N} \widetilde{\theta_{IJ}^{g}}(H) = 1 \text{ ve } \sum_{i,j=1}^{N} \widetilde{\theta_{ij}^{g}}(H) = N \tag{6}$$

$$\widetilde{\theta_{ij}^{g}}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{K} \theta_{ij}^{g}(H)} \tag{7}$$

Diebold and Yilmaz (2012) show the total diffusion index of volatility shocks obtained from the variance decomposition of the KPPS forecast error in Equation (8).

$$S^{g}(H) = \frac{\sum_{i,j=1}^{N} \widetilde{\theta_{ij}^{g}}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta_{ij}^{g}}(H)} \times 100 \tag{8}$$

The volatility total dispersion index, which shows the directional dispersion from market (i) to market (j), is given in Equation (9).

$$S_{i\leftarrow j}^{g}(H) = \frac{\sum_{i\neq j=1}^{N} \widetilde{\theta_{ij}^{g}}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta_{ij}^{g}}(H)N} \times 100 \tag{9}$$

Similar to Equation (7), the directional volatility spillovers from market (i) to all other markets (j) are shown in Equation (10).

$$S_{i\rightarrow j}^{g}(H) = \frac{\sum_{i\neq j=j}^{N} \widetilde{\theta_{ij}^{g}}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta_{ji}^{g}}(H)} \times 100 \tag{10}$$

Finally, the difference between the gross volatility shocks transmitted from market (i) to all markets (j) is calculated as net directional volatility spillovers in Equation (11).

$$S(H) = S_{i\rightarrow j}^{g}(H) - S_{i\leftarrow j}^{g}(H) \tag{9}$$

$$S_{ij}^{g}(H) = \left[\frac{\widetilde{\theta_{ji}^{g}}(H)}{\sum_{i.k=1}^{K} \widetilde{\theta_{ik}^{g}}(H)} - \frac{\widetilde{\theta_{ji}^{g}}(H)}{\sum_{j.k=1}^{K} \widetilde{\theta_{ik}^{g}}(H)}\right] \times 100 = \left[\frac{\widetilde{\theta_{ji}^{g}}(H) - \widetilde{\theta_{ij}^{g}}(H)}{N}\right] \times 100 \tag{12}$$

Equation (12) shows the net bilateral volatility spillovers between markets (i) and (j), gross volatility shocks transmitted from market (i) to market (j) and gross volatility shocks transmitted from market (j) to market (i).

4. FINDINGS

This section presents the findings from the volatility spillover analysis conducted using the Diebold and Yilmaz (2012) methodology. First, descriptive statistics for Bitcoin, Ethereum, and Altcoin indices are reported. The Marketing index exhibits the highest standard deviation (0.106), indicating elevated volatility, whereas Bitcoin has the lowest (0.037), reflecting comparatively greater stability.

Next, the Augmented Dickey–Fuller (ADF) test is employed to assess stationarity. At the 1% significance level, all variables are stationary in levels. The optimal lag length for the VAR model is determined using the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan–Quinn (HQ) criterion. Based on the AIC, a lag length of one is selected; subsequent analysis uses a VAR(1) with generalized forecast error variance decompositions under the Diebold–Yilmaz connectedness framework.

Table 2. Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Sum	Sum Sq. Dev.
ANALYTICS	0.001748	-0.000245	0.555569	-0.326049	0.079261	1.352164	11.36666	2557.816	0.000000	1.387827	4.981914
BITCOIN	0.000351	0.000000	0.192491	-0.158441	0.037145	0.044575	5.821558	263.6457	0.000000	0.278996	1.094113
DEFI	0.001070	0.001826	0.300613	-0.310980	0.053046	-0.120033	6.600725	430.8394	0.000000	0.849601	2.231392
ETHEREUM	0.002167	0.000736	0.245335	-0.263026	0.049030	-0.016020	6.476859	399.9635	0.000000	1.720205	1.906316
GAMING	0.006768	-0.003782	0.749952	-0.370504	0.089551	1.777883	12.93852	3686.068	0.000000	5.374050	6.359336
HEALTH	0.000804	0.001404	0.539825	-0.323637	0.065364	0.814963	13.64163	3834.389	0.000000	0.638256	3.388026
IDENTITY	0.001896	-0.004228	0.483223	-0.276811	0.072481	1.197163	8.991325	1377.218	0.000000	1.505470	4.166068
IIOTCOIN	0.003996	-0.000250	0.846860	-0.246144	0.081082	1.789749	18.03089	7898.328	0.000000	3.172995	5.213443
LOGISTICS	0.004057	0.002419	0.336716	-0.329734	0.071759	0.139446	5.625837	230.6835	0.000000	3.221577	4.083406
MARKETING	0.005597	9.62E-05	0.659615	-0.435141	0.105925	1.032040	10.22375	1867.324	0.000000	4.443842	8.897571
MEMESCOIN	0.001964	0.000194	0.903482	-0.533899	0.080201	1.734112	29.24621	23187.84	0.000000	1.559673	5.100706
METAVERSE	0.003356	-0.001431	0.465087	-0.388651	0.077273	0.848994	8.263368	1011.894	0.000000	2.664500	4.735036
MUSIC	0.004452	0.000645	0.731576	-0.370483	0.085182	1.522550	13.50008	3954.264	0.000000	3.535116	5.754001
NFT	0.003530	-0.002436	0.673947	-0.355280	0.079280	1.480603	12.79509	3464.238	0.000000	2.802958	4.984312
PRIVACY	0.001347	0.002533	0.263245	-0.385439	0.050989	-0.315368	10.97232	2115.868	0.000000	1.069700	2.061699
STABLECOIN	6.81E-07	-1.47E-07	0.009166	-0.009422	0.002133	-0.116739	6.018526	303.2422	0.000000	0.000541	0.003606
STROGE	0.001113	-0.002205	0.815910	-0.339929	0.073980	2.576779	27.99403	21545.88	0.000000	0.883972	4.340077
TOURISM	0.001344	0.001264	0.492148	-0.388852	0.054711	0.617247	15.84585	5509.691	0.000000	1.067336	2.373665
WALLET	0.002564	-0.001244	0.379362	-0.356802	0.073877	0.565418	6.906498	547.1822	0.000000	2.035732	4.328059
WEB3	0.001009	0.000844	0.241595	-0.362884	0.057162	-0.160926	6.861269	496.6796	0.000000	0.801370	2.591080

Table 3. ADF Unit Root Test Results

Variables	Level Values	
	Constant	Constant and Trend
Bitcoin	-28.605 (0)*	-28.618(0)*
Ethereum	-28.632(0)*	-28.747(0)*
Analytics	-26.751(0)*	-26.780(0)*
Defi	-24.257(0)*	-24.316(0)*
Gaming	-23.243(0)*	-23.508(0)*
Health	-22.526(0)*	-22.532(0)*
Identity	-24.873(0)*	-24.863(0)*
Iiotcoin	-25.539(0)*	-25.823(0)*
Logistics	-26.125(0)*	-26.146(0)*
Marketing	-32.585(0)*	-32.568(0)*
Memescoin	-14.488(2)*	-14.556(2)*
Metaverse	-24.343(0)*	-24.451(0)*
Music	-26.603(0)*	-26.762(0)*
Nft	-23.028(0)*	-23.145(0)*
Privacy	-31.110(0)*	-31.139(0)*
Stablecoin	-20.928(4)*	-20.913(4)*
Stroge	-27.058(0)*	-27.105(0)*
Tourism	-28.604(0)*	-28.818(0)*
Wallet	-26.792(0)*	-26.945(0)*
Web3	-28.594(0)*	-28.699(0)*
Critical Values		
a = % 1*	-3.438	-3.969
b= % 5	-2.864	-3.415
c= % 10	-2.568	-3.129
*: Analyzed at 1% significance level.		

When the ADF Unit Root Test results are analyzed, it is found that all variables are statistically stationary at level value at 1% significance level. After the stationarity test of the variables, it is necessary to determine the appropriate lag length for the volatility spillover analysis. For this purpose, AIC, SC and HQ information criteria, which will be the basis for determining the lag length, are determined by making use of the VAR model created with the variables subject to analysis and presented in Table 4.

Table 4. Lag Lengths

Number of Delay	AIC	SC	HQ
0	-71.49910	-71.38035*	-71.45345
1	**-72.53054***	**-70.03674**	**-71.57174***
2	-72.37726	-67.50842	-70.50532
3	-72.29327	-65.04940	-69.50818
4	-72.15613	-62.53721	-68.45790
5	-71.96130	-59.96734	-67.34993
6	-71.81061	-57.44161	-66.28609
7	-71.74976	-55.00572	-65.31210
8	-71.52837	-52.40929	-64.17757

When the appropriate lag lengths were analyzed, the lag length with the lowest AIC, SC, HQ information criterion was determined as 1. The analysis was conducted with the lowest lag length of the AIC information criterion, which is 1. The analysis continued with the related VAR (1,1) model. With the appropriate lag length determined, the results of the Diebold-Yılmaz analysis conducted to determine the volatility spillovers between the variables are shown in Table 5.

Table 5. Volatility Spread Index

	BITCOIN	ETHEREUM	ANALYTICS	DEFI	GAMING	HEALTH	IDENTITY	IIOTCOIN	LOGISTICS	MARKETING	MEMESCOIN	METAVERSE	MUSIC	NFT	PRIVACY	STABLECOIN	STROGE	TOURISM	WALLET	WEB3	From Others
BITCOIN	97.6	0.4	0.1	0.1	0.0	0.0	0.0	0.0	0.7	0.3	0.1	0.1	0.0	0.0	0.2	0.4	0.0	0.0	0.0	0.0	2.4
ETHEREUM	65.3	32.4	0.1	0.1	0.2	0.0	0.0	0.4	0.2	0.1	0.0	0.0	0.0	0.0	0.6	0.2	0.0	0.2	0.0	0.0	67.6
ANALYTICS	27.9	7.9	62.2	0.0	0.0	0.1	0.0	0.2	0.3	0.0	0.0	0.0	0.0	0.1	0.6	0.0	0.2	0.1	0.1	0.1	37.8
DEFI	62.3	8.0	1.8	25.1	0.4	0.1	0.2	0.1	1.0	0.1	0.0	0.0	0.1	0.1	0.5	0.1	0.1	0.1	0.1	0.1	74.9
GAMING	25.8	4.7	1.6	2.2	62.5	0.3	0.0	0.2	0.4	0.2	0.0	0.1	0.0	0.0	0.4	0.1	0.0	1.0	0.1	0.2	37.5
HEALTH	24.6	3.8	1.8	0.7	0.3	63.2	0.0	0.0	0.7	0.0	0.0	0.1	0.0	0.3	0.0	0.4	3.3	0.1	0.2	0.3	36.8
IDENTITY	25.4	5.5	3.1	2.7	0.2	1.0	59.8	0.2	0.3	0.0	0.3	0.1	0.0	0.1	0.9	0.0	0.1	0.1	0.0	0.0	40.2
IIOTCOIN	24.6	2.9	1.1	2.3	0.7	0.9	0.7	61.2	3.0	0.2	0.1	0.0	0.1	0.1	1.4	0.2	0.4	0.0	0.1	0.0	38.8
LOGISTICS	43.4	6.2	1.5	2.2	0.4	0.3	1.0	1.3	41.7	0.0	0.1	0.2	0.1	0.1	0.5	0.3	0.1	0.1	0.6	0.0	58.3
MARKETING	15.2	12.3	0.3	0.4	0.5	0.2	0.5	1.4	0.3	67.9	0.0	0.0	0.1	0.1	0.0	0.4	0.1	0.1	0.1	0.0	32.1
MEMESCOIN	18.8	1.4	1.6	0.7	0.2	0.6	0.6	0.3	0.3	0.0	74.4	0.2	0.0	0.2	0.3	0.2	0.0	0.0	0.0	0.0	25.6
METAVERSE	34.0	2.5	1.0	1.8	29.7	0.5	0.3	0.6	0.2	0.4	0.5	26.2	0.0	0.7	0.5	0.0	0.1	0.6	0.2	0.2	73.8
MUSIC	23.5	3.0	2.2	1.1	1.1	0.3	0.2	0.9	0.0	0.5	0.3	0.3	65.2	0.4	0.3	0.0	0.4	0.1	0.1	0.0	34.8
NFT	31.3	6.5	2.2	2.3	35.1	0.2	0.5	0.6	0.3	0.3	0.2	3.1	0.0	15.6	0.7	0.2	0.1	0.5	0.2	0.0	84.4
PRIVACY	52.6	4.7	0.9	0.6	0.5	0.5	0.7	0.1	1.0	0.0	1.5	0.5	0.2	0.5	35.4	0.2	0.0	0.0	0.0	0.2	64.6
STABLECOIN	3.2	0.1	0.3	1.9	0.6	0.2	0.0	0.0	0.0	0.1	0.1	0.3	0.8	0.4	0.0	91.9	0.1	0.0	0.1	0.0	8.1
STROGE	33.9	2.3	3.0	2.5	0.5	0.9	3.3	0.7	0.7	0.0	0.3	1.6	0.5	0.5	0.7	0.5	47.8	0.3	0.0	0.0	52.2
TOURISM	20.9	4.5	3.3	0.4	0.5	0.4	0.8	0.0	0.2	0.4	0.1	0.2	0.5	0.2	0.3	0.2	0.4	66.5	0.0	0.0	33.5
WALLET	33.5	8.7	3.3	2.3	1.5	0.7	0.2	0.5	0.9	0.1	0.2	0.1	0.3	0.2	0.4	0.3	0.4	0.3	45.8	0.3	54.2
WEB3	54.9	8.9	3.6	3.8	0.3	0.6	1.1	0.8	0.9	0.1	0.5	0.9	0.3	0.2	0.7	0.2	3.4	0.7	0.0	18.0	82.0
Contribution to others	621.1	94.2	32.9	28.2	72.6	7.7	10.2	8.4	11.6	3.0	4.4	7.8	3.2	4.1	8.9	4.0	9.2	4.4	1.9	1.6	939.4
Contribution including own	718.7	126.6	95.0	53.3	135.2	70.9	70.0	69.6	53.3	70.9	78.9	33.9	68.5	19.8	44.2	95.9	57.0	70.9	47.8	19.6	47.0%

When Table 4 is analyzed, it is seen that the volatility spread ratio of the VAR model, which shows the share of external shocks in total shocks, is 47%. This implies that external shocks cause more than 47% of the volatility in cryptocurrency markets and shows that mutual interactions significantly cause the volatility in the cryptocurrency market. The fact that the volatility diffusion index is close to 50% indicates that market participants should be careful in their risk management. This underscores that the market is highly interconnected, and any large-scale shock can lead to widespread volatility. Given the market's high interconnectivity and susceptibility to systemic shocks, regulators and investors should ensure market stability and develop portfolio diversification strategies.

The analysis reveals that the volatility spread in the cryptocurrency market is concentrated among certain assets. Bitcoin and Ethereum stand out as the two assets with the highest level of volatility spread across the market. Bitcoin's contribution to the total volatility spread over the cryptocurrencies included in the analysis is 621.1%, while Ethereum's contribution is 94.2%. This shows that while Bitcoin is the main driver, the impact of the leading cryptocurrencies on the overall market is quite strong. Overall, this suggests that most of the volatility spread is driven by the market's largest assets, while small and mid-cap tokens are exposed to higher exogenous volatility. Bitcoin explains 97.6% of its own internal volatility in the model, spreading 2.4% volatility to other cryptocurrencies. Ethereum, on the other hand, has 32.4% of its own internal volatility and spreads 67.6% to other assets. This finding suggests that Ethereum has more external influence on the transmission of volatility within the market than Bitcoin. It also suggests that Bitcoin's volatility is largely driven by internal dynamics, while Ethereum's volatility is more influenced by other assets in the market.

Among thematic categories, it is observed that Metaverse, NFT, and Web3 assets exhibit significant levels of volatility spillover. Particularly, the Metaverse (73.8%) and NFT (84.4%) sectors are largely exposed to external volatility shocks. In the DeFi category, the total volatility spillover contribution is calculated as 74.9%, indicating that volatility within the decentralized finance ecosystem is largely driven by external factors.

It is also found that the logistics (58.3%), music (34.8%), and health (36.8%) categories exhibit a more balanced volatility structure compared to other thematic groups. The relatively lower exposure of these categories to external volatility suggests that the projects in these areas may be built on more solid market fundamentals. Notably, tokens in the health and logistics sectors have been observed to be more resilient to external shocks.

According to the results of the analysis, the assets with the lowest external volatility spillover are stablecoins. The stablecoin category explains 91.9% of its own internal volatility and is minimally exposed to external effects, demonstrating the resilience of stablecoins against market-wide volatility. Apart from stablecoins, the identity (40.2%), industrial IoT (38.8%), and marketing (32.1%) categories also appear among the assets with relatively low exposure to external volatility.

When examining the extent to which altcoin groups influence other altcoin groups, the following spillover effects are observed: Analytics (32%), DeFi (28%), Gaming (72%), Health (7%), Identity (10%), IoT (8%), Logistics (8%), Memecoins (4%), Marketing (3%), Metaverse

(7%), Music (3%), NFT (4%), Privacy (8%), Stablecoins (4%), Storage (9%), Tourism (4%), Wallet (1%), and Web3 (1%).

Conversely, the degree to which altcoin groups are influenced by other altcoin groups is as follows: Analytics (37%), DeFi (74%), Gaming (37%), Health (36%), Identity (40%), IIoT (38%), Logistics (58%), Memecoins (25%), Marketing (32%), Metaverse (73%), Music (34%), NFT (84%), Privacy (64%), Stablecoins (8%), Storage (52%), Tourism (33%), Wallet (54%), and Web3 (82%).

Among the altcoin groups, the ones exerting the strongest influence on others are Gaming (72%), Analytics (32%), and DeFi (28%), while the effects of the others remain at or below 10%. The groups most influenced by other altcoin groups include NFT (84%), Web3 (82%), DeFi (74%), Metaverse (73%), Privacy (64%), Logistics (58%), Storage (52%), and others below 40%.

According to the analysis, Bitcoin is affected by its own shocks at a rate of 97.6%, while the remaining 0.4% of its volatility comes from Ethereum and stablecoins. Ethereum is influenced by its own shocks at a rate of 32.4%, and externally, it is primarily affected by Bitcoin (65.3%) and, to a much lesser extent, by IoT Coin (0.4%) and Privacy (0.6%) altcoin groups.

When examining the impact of Bitcoin shocks on altcoin groups, the following levels of influence are observed: Analytics (27.9%), DeFi (62.3%), Gaming (25.8%), Health (24.6%), Identity (25.4%), IoT Coin (24.6%), Logistics (43.4%), Marketing (15.2%), Memecoins (18.8%), Metaverse (34%), Music (23.5%), Privacy (52.6%), Stablecoins (3.2%), Storage (33.9%), Tourism (20.9%), Wallet (33.5%), and Web3 (54.9%).

In terms of Ethereum shocks, the levels of impact on altcoin groups are as follows: Analytics (7.9%), DeFi (8%), Gaming (4.7%), Health (3.8%), Identity (5.5%), IoT Coin (2.9%), Logistics (6.2%), Marketing (12.3%), Memecoins (1.4%), Metaverse (2.5%), Music (3%), Privacy (6.5%), Stablecoins (4.7%), Tourism (2.3%), Wallet (8.7%), and Web3 (8.9%).

NFT altcoin groups are affected primarily by their own internal shocks and do not exhibit any significant influence on or from Bitcoin and Ethereum. NFTs are typically traded among smaller communities and investors, which limits the impact of broader market shocks. This finding aligns with Ammous (2018), who states that NFTs generally form a niche market, with the coins in this space operating independently of major market variables like Bitcoin and Ethereum.

Ji et al. (2019) also found low volatility between coins in the stablecoin category such as Ripple, Litecoin, Stellar, and Dash and Bitcoin and Ethereum, which is consistent with the current findings.

To provide a summary of volatility during the study period, a total volatility spillover graph was constructed based on the results of the Diebold and Yilmaz analysis using the VAR (1,1) model. To avoid missing significant breakpoints, the graph was generated using a 200-day rolling window, recalculating the variables continuously and observing their changes over time. The total volatility spillover graph for the model is presented in Figure 1.

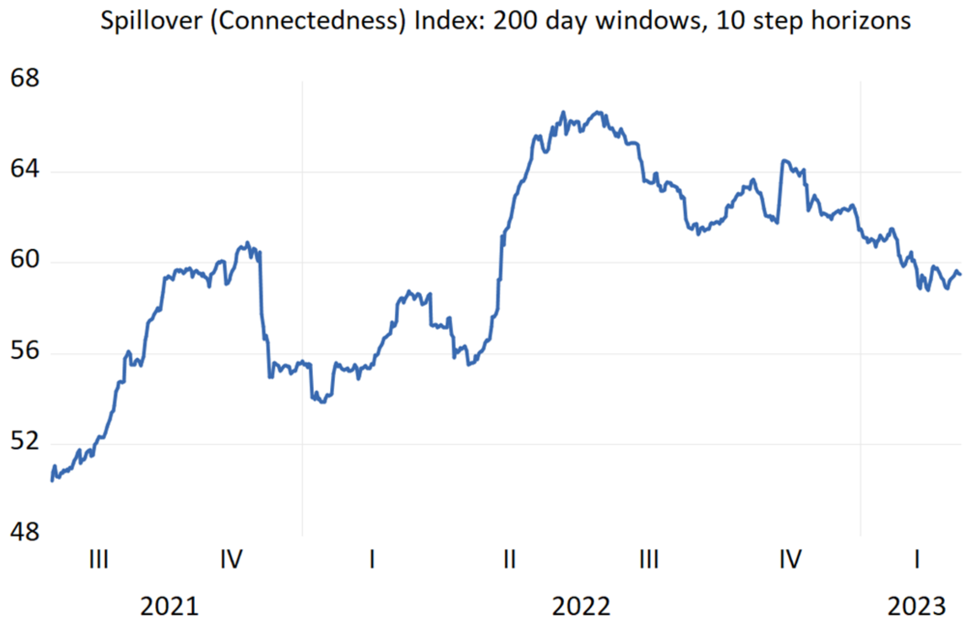

Figure 1. Graph of Total Volatility Spillovers

Upon examining Figure 1, a significant increase in volatility is observed in the third quarter of 2021, followed by a decrease in the fourth quarter. A notable rise is again recorded in the second quarter of 2022, with a partial decline emerging from the third quarter onward.

An analysis of the relevant periods reveals that in 2021, the purchase of $1.5 billion worth of Bitcoin by Tesla, alongside Ethereum's transition to the Proof-of-Stake system with the implementation of the 2.0 update—which bolstered market confidence—stimulated considerable interest from institutional investors, resulting in a substantial market uptrend.

In contrast, in 2022, the bankruptcy of the cryptocurrency exchange FTX and the collapse of UST, the stablecoin of the Terra (Luna) ecosystem, which wiped out approximately $60 billion in market value, led to a severe loss of confidence in stablecoins and their underlying algorithms, resulting in significant negative repercussions for the market.

In the early months of 2022, the heightened interest in NFTs, such as Bored Ape Yacht Club and Crypto Punks, as well as cryptocurrencies based on music, collectibles, and digital art, contributed to a surge in volatility. The growing popularity of metaverses, combined with Facebook's rebranding to "Meta," further fueled this interest and led to an expedited increase in cryptocurrency market volatility.

Towards the end of 2022, the onset of global inflation and the subsequent tightening of monetary policies by central banks, coupled with the eruption of the Russia–Ukraine conflict, had an adverse impact on cryptocurrency markets, resulting in a notable reduction in market volatility.

5. CONCLUSION

Cryptocurrencies have long been the subject of significant interest from various individuals across different platforms. Every day, the number of people becoming aware of cryptocurrencies increases, and individuals are gaining more insight into how these currencies operate. While some support the existence of cryptocurrencies and discuss their benefits, others offer critical comments about them. One of the ongoing debates surrounding cryptocurrencies is whether they truly function as a currency or whether they can be considered as an investment asset. Despite the numerous debates on cryptocurrencies, the volume of research in this field remains relatively limited. The aim of this study was to investigate the effects of volatility spillover between Bitcoin, Ethereum, and altcoins.

This study reaffirms the central roles of Bitcoin and Ethereum in the cryptocurrency market. Bitcoin emerges as the most influential asset, while Ethereum maintains its position as the second most impactful asset after Bitcoin. When examining the shock effects on altcoins, it was observed that most altcoins are most affected by Bitcoin's shocks following their own. The study also revealed that the highest return was in the Memes Coin group at 0.903%, while the highest volatility was in the Marketing group at 0.105%. Stablecoins, on the other hand, were identified as the group with the lowest volatility at 0.002%.

In the first quarter of 2022, referred to as the "crypto winter," it was observed that the influence of Bitcoin and Ethereum on altcoin groups significantly decreased. During this period, events such as the Ukraine war, the tightening monetary policies of the FED post-pandemic, and cyberattacks on DeFi platforms increased market pressures, limiting the impact of Bitcoin and Ethereum's volatility shocks on altcoin groups. These changes also highlight that the cryptocurrency market is not only a financial investment tool but an ecosystem shaped by rapidly evolving technologies.

Volatility spillover in cryptocurrency markets is predominantly shaped by the effects of leading cryptocurrencies such as Bitcoin and Ethereum. While Bitcoin has a high level of internal volatility, its impact on the broader market is relatively limited. In contrast, Ethereum's volatility spillover is broader, and it has a more significant influence on market-wide price fluctuations.

From a thematic category perspective, it was found that metaverse, NFT, and Web3 assets are more sensitive to external volatility. These assets demonstrate a more fragile structure in response to investor sentiment and market fluctuations. On the other hand, certain categories, such as stablecoins, identity-themed tokens, and marketing-themed tokens, exhibit more stable volatility dynamics.

The findings of this study have significant implications for risk management strategies in cryptocurrency markets. Assets that are exposed to high external volatility need to be carefully evaluated when making investment decisions. Furthermore, the volatility dynamics of market-leading assets such as Bitcoin and Ethereum serve as an important indicator for understanding broader market movements. Future research could contribute to a deeper understanding of the market by examining how volatility spillover changes under different periods and market conditions.

In conclusion, the central roles of Bitcoin and Ethereum in the cryptocurrency market have been reaffirmed, and it has been shown that altcoin groups are largely influenced by these two assets in terms of volatility and return. Additionally, it is clear that different cryptocurrency asset groups require different strategic approaches due to their distinct risk and return profiles. Accordingly, Bitcoin and Ethereum investors should consider the past data and shock effects between these two assets, while altcoin investors should understand the volatility structures of their respective groups. By utilizing the findings of this study, investors can make more effective and informed decisions by monitoring assets that serve as leading indicators in the cryptocurrency market. In doing so, they can increase their returns while minimizing their risks.

DECLARATION OF THE AUTHORS

Ethical approval and consent to participate: Scientific content and ethical rules have been obeyed in this study.

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