Co-movements of the top cryptocurrencies: new insights from wavelet coherence analysis

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Abstract:

This paper makes use of wavelet coherence analysis to investigate dynamic co-movements between the most prominent cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Tether (TETH), and Ripple (XRP), based on market capitalization utilizing daily prices from 1 January 2018 to 20 May 2025. The analysis reveals new insights into multi-scale connections and uncovers heterogeneous synchronization patterns. The Bitcoin with Ethereum and Bitcoin with Binance pairs demonstrate robust and stable coherence underpinned by market-specific and system-related factors. The relationship between Bitcoin and Tether appears weaker and counter-cyclical, serving to identify the stabilizing influence of Tether. The event-driven nature of the coherence between Bitcoin and Ripple, primarily driven by regulatory news, rounds out the results. These results shed light on system risk and influence diversification strategies and regulatory intervention across cryptocurrency markets..

Keywords:

Co-movement, COVID-19, cryptocurrencies, Wavelet

JEL classification: G11; G15.

1. Introduction:

The emergence of cryptocurrencies as a transformative force in global finance has sparked an increasing amount of research focused on understanding their market behavior, systemic relevance, and interdependencies, transforming the use of online applications (Parameswaran et al., 2024). Since the launch of Bitcoin (BTC) in 2009, the cryptocurrency ecosystem has evolved into a multi-trillion-dollar market comprising thousands of digital assets. Among them, a select group—namely Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Tether (TETH), and Ripple (XRP)—has consistently ranked among the top in terms of market capitalization, trading volume, and network utility. These assets serve diverse roles: BTC as a digital store of value, ETH as the foundation of Decentralized Finance (DeFi), BNB as the utility token for the Binance ecosystem, TETH as the leading stablecoin for liquidity provision, and XRP as a cross-border settlement token. Together, they shape the core structure of the crypto-financial landscape.

It is crucial for various stakeholders, ranging from institutional investors to portfolio managers, regulators to policymakers, to understand co-movement patterns among these top cryptocurrencies. High levels of synchronization can signal system risk and reduce diversification benefits (Nguyen et al., 2025; Han et al., 2024; Kayani et al., 2024). On the other hand, frequency-specific co-movements could suggest market segmentation, behavioral heterogeneity, and shock propagation. Prior research has overwhelmingly used static measures of correlation, Granger causality, and vector autoregression models, which could mask the inherent temporal and spectral complexities of cryptocurrency markets (Saâdaoui & Rabbouch, 2025; Moni et al., 2025; Hamouda et al., 2024; Khalfaoui et al., 2023).

Building on the scholarly contributions in the fields of financial inclusion (Rani, 2025; Del Sarto & Ozili, 2025; Eshun & Kočenda, 2025; Syed, 2025; Kebede et al., 2025; Qizam et al., 2025; Sarma & Pais, 2011), digital assets (Kayani et al., 2025; Zalan & Toufaily, 2025; Hernando-Corrochano et al., 2025; Ali et al., 2024), and cryptocurrency (Symss, 2025; Nim et al., 2025; Ding et al., 2025), wavelet analysis in cryptocurrency markets (Alvarez-Ramirez et al., 2025; Álvarez et al., 2025; Shu et al., 2025; Moni et al., 2025), this paper aims to enhance the empirical investigation of inter-cryptocurrency dynamics by employing wavelet coherence analysis. This non-linear, time-frequency technique allows for a multi-resolution decomposition of co-movement structures. Wavelet coherence provides a powerful lens for detecting both short-term and long-term co-dependencies, localized in time and across investment horizons. Unlike traditional correlation methods, this approach captures transient, evolving, and multi-scale interactions that are particularly relevant in markets characterized by high volatility, external shocks (e.g., regulatory actions, security breaches), and endogenous cycles of speculation and innovation.

This study aims to focus on three folds using daily price data from 2018 to 2025 for BTC, ETH, BNB, TETH, and XRP. First, map the dynamic co-movement structure among the top five cryptocurrencies. Second, identify periods and frequency bands where their interrelationships intensify or weaken. Third, explore the implications for systemic stability and optimal asset allocation. Particular attention is given to market events such as the COVID-19 crash, the Russian-Ukrainian conflict, and the recent Trump tariffs

This research contributes to the growing literature on cryptocurrency interconnectivity by integrating high-frequency empirical techniques with theoretical insights from complex systems and financial contagion. Using wavelet coherence analysis, the findings shed light on the co-movements of the top cryptocurrencies, giving new insights. First, it reveals that BTC–ETH and BTC–BNB pairs exhibit strong and persistent co-movements. BTC–ETH reflects systemic interdependence, and BTC–BNB is influenced by exchange-specific and DeFi-driven dynamics. Second, the BTC–TETH coherence shows a weaker, counter-cyclical, and emerges mainly during periods of market stress, highlighting the stabilizing role of Tether. Third, BTC–XRP displays sporadic and event-driven coherence, often shaped by regulatory developments, with limited long-term coupling to Bitcoin. The results demonstrate heterogeneous synchronization patterns across leading cryptocurrencies, shaped by market function, structural positioning, and external shocks. The findings offer practical value for developing resilient investment strategies, monitoring digital financial infrastructure, and guiding macroprudential oversight in an era of increasing crypto-financial integration.

The structure of this paper is as follows: Section 2 provides the literature review. Section 3 discusses the methodology used in the study. Section 4 describes the return series data and presents the descriptive statistics. Section 5 discusses the results and findings. Finally, Section 6 concludes.

2. Literature review:

The evolving landscape of cryptocurrency markets has garnered increasing scholarly attention, particularly concerning the interrelationships among major digital assets. Cryptocurrencies have been used as a legal way of payment (Cointelegraph, 2017); certain central banks are investigating the usage of cryptocurrencies; and a large number of businesses and banks formed the Enterprise Alliance to employ cryptocurrencies and related technology. Moreover, the Chicago Mercantile Exchange (CME) began negotiating BTC futures in 2017. Early studies primarily focused on Bitcoin's price dynamics and speculative behavior (Alvarez-Ramirez et al., 2025; Antar, 2025; Yadav, 2024). As the ecosystem matured, research extended to multivariate relationships between cryptocurrencies, with notable contributions analyzing correlations (Queiroz et al., 2024; Shi et al., 2020; Aslanidis et al., 2019), Granger causality (Zhang et al., 2025; Huang, 2024), and portfolio diversification implications (Wang et al., 2025; Lamine et al., 2024).

Despite these advances, conventional econometric methods often assume linearity and time-invariance, which are misaligned with the inherent features of crypto markets marked by volatility clustering, abrupt structural breaks, and non-stationarity. This has increased interest in time-frequency domain methods, especially wavelet-based analyses. In addition to wavelet-based methods, several studies have applied Vector Error Correction Models (VECM) and Impulse Response Function (IRF) analyses to investigate both short-term dynamics and long-term equilibrium relationships among cryptocurrencies and between crypto and traditional assets. These methods enable researchers to observe cointegration among non-stationary price series and track, over time, the cross-market reactions to shocks. VECM models, e.g., have been employed by Chowdhury and Abdullah (2024), Malladi (2023), Huynh et al. (2022), and Abraham (2020) to identify long-run relationships and quantify short-run adjustments between leading cryptocurrencies. Such models are valuable in providing information related to deriving price discovery, market integration, and potential contagion transmission channels. While our study focuses on wavelet coherence to capture time-frequency-localized co-movements, integrating VECM and IRF analyses offers a complementary econometric perspective on interdependencies in cryptocurrency markets.

To capture higher-dimensional dependence structures in financial markets, researchers have increasingly employed multivariate wavelet coherence, in addition to bivariate wavelet coherence investigations. For instance, Al-Yahyaee et al. (2019) utilize multivariate wavelet coherence to examine the interdependencies between energy commodities and cryptocurrencies in the context of geopolitical concerns, while Lahmiri and Bekiros (2019) investigate multiscale volatility spillovers across key cryptocurrencies. Such multivariate frameworks enable richer insights into market contagion and systemic risk. To enhance prediction and classification, hybrid models that combine wavelet transforms with machine learning approaches are also gaining popularity. For example, Alrumaih and Al-Fawzan (2022) integrate wavelet denoising with support vector machines for financial time series forecasting, and Parameswaran et al. (2024) employ wavelet decomposition in conjunction with deep learning to predict cryptocurrency trends. These hybrid methods offer intriguing avenues for examining intricate and changing market dynamics by utilizing machine learning's capacity for non-linear pattern identification and wavelets' ability to extract time-frequency characteristics. Wavelet coherence, in particular, allows researchers to investigate co-movement patterns that are both time- and frequency-localized, providing a nuanced lens into lead-lag relationships and multiscale dependencies. Notable examples in the energy markets include Husain et al. (2024), Ahmed (2022), and Vacha and Barunik (2012), who applied wavelet coherence to cryptocurrency markets, revealing episodic connectedness during crises. However, many of these studies are limited to pairwise analyses or exclude key actors such as stablecoins (e.g., Tether), which play a critical role in liquidity flows and arbitrage.

This paper builds on and extends this literature by including both volatile (BTC, ETH, BNB, XRP) and non-volatile (TETH) assets. It focuses on dynamic, multi-scale dependencies across crisis and stable periods, offering a broader temporal window (2018–2025) that captures major market disruptions and regulatory changes.

3. Methodology :

The wavelet coherence analysis typically uses a Continuous Wavelet Transform (CWT). The most commonly employed wavelet in coherence analysis is the Morlet wavelet due to its good frequency resolution and smooth time-frequency localization. The selection of the Morlet wavelet is due to its ability to provide a well-balanced compromise between time and frequency resolution, making it especially effective for analyzing financial time series characterized by smooth, continuous cycles and non-stationary behavior. Its structure enables clear identification of local oscillatory patterns at different scales. By comparison, the Haar wavelet has excellent time localization but inferior frequency resolution due to its discontinuous, step-like form, which makes it less effective for uncovering smooth co-movement dynamics. Similarly, while Daubechies wavelets are popular in discrete applications for their compact support and orthogonality, their asymmetric and less intuitive shapes are not ideally suited for continuous wavelet coherence analysis. Because of its ability to highlight both short-term fluctuations and long-term trends in a clear and interpretable manner, the Morlet wavelet is widely recommended for coherence studies in economics and finance.

The Morlet wavelet is given by:

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\frac{\eta^2}{2}}$$

where:

η is the dimensionless time parameter.

ω_0 is the nondimensional frequency parameter (often chosen as for a good trade-off between time and frequency localization.

$\pi^{-1/4}$ is the normalization factor ensuring unit energy.

The wavelet transform of a time series **x(t)** at scale and translation **s** is defined **τ** as:

$$W_x(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t)\, \psi^*\left(\frac{t-\tau}{s}\right) dt$$

where:

$W_x(s,\tau)$ is the wavelet coefficient.

s is the scale parameter (inversely related to frequency).

τ is the translation parameter (time shift).

ψ^* is the complex conjugate of the wavelet function.

The coherence between two time series $x(t)$ and $y(t)$ at scale and time τ is:

$$R_{xy}^2(s,\tau) = \frac{\left|S\left(s^{-1}W_{xy}(s,\tau)\right)\right|^2}{S\left(s^{-1}|W_x(s,\tau)|^2\right) \cdot S\left(s^{-1}|W_y(s,\tau)|^2\right)}$$

where:

$W_{xy}(s,\tau) = W_x(s,\tau)W_y^*(s,\tau)$ is the cross-wavelet transform.

$S(\cdot)$ indicates a smoothing operator in time and scale.

$R_{xy}^2(s,\tau)$ the wavelet coherence, ranging from (no coherence) to (perfect coherence).

Coherence close to indicates a strong relationship between the two series at the given scale (frequency) and time. Coherence close to indicates little to no relationship.

The Morlet wavelet is typically chosen for financial and economic data due to its effective handling of non-stationary signals and clear interpretability of results.

4. Data and preliminary analysis:

This study applies the wavelet method of Grinsted et al. (2004) to daily data of the top five crypto (based on market capitalization): Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Tether (TETH), and Ripple (XRP) from January 1, 2018, to May 20, 2025. The data were collected from Investing.com. The data from Investing.com is widely utilized and is a reputable financial data platform. While the data are aggregated from major exchanges and are commonly referenced in academic research, it is important to note that minor discrepancies can exist across different data providers due to variations in aggregation methods, coverage, and reporting standards. Although these differences do not materially affect the main findings, we acknowledge that reliance on a single data provider may introduce some measurement bias or fail to capture idiosyncratic pricing anomalies present on less prominent trading platforms. This time from captures a series of major events and turning points, including the aftermath of the 2017 Bitcoin rally, the evolution and widespread adoption of DeFi protocols, the COVID-19 pandemic and its impact on financial markets, heightened regulatory scrutiny in multiple jurisdictions, and significant episodes of market turbulence such as the 2021 bull run, the collapse of several crypto platforms, and ongoing legal and policy developments affecting major assets like Ripple and Tether. Extending the analysis through 2025 allows us to incorporate the most recent data and account for the ongoing integration of digital assets into the global financial system. Our study observes not only routine market fluctuations but also the response of co-movement patterns to structural changes and external shocks, thus offering a more complete and policy-relevant analysis.

Figure 1 illustrates the dynamics of prices and returns, demonstrating temporal evolution in prices and returns for five leading cryptocurrencies. The assets cover non-overlapping functional categories in the cryptocurrency market, ranging from decentralized computing platforms (BTC, ETH) to tokens native to exchanges (BNB) and fiat-collateralized stable coins (TETH), and together provide a representative cross-section of market dynamics. Price dynamics demonstrate significant heterogeneity among these assets. The most capitalized cryptocurrencies, Bitcoin and Ethereum, are highly volatile with frequent, large price movements. The fluctuations align with their responsiveness to macro variables, investor sentiment, and speculative trading. Ethereum, while tracking Bitcoin's volatility, at times breaks out due to network-specific drivers like decentralized finance (DeFi) growth and protocol upgrades (the move to proof-of-stake consensus, for example). BNB exhibits moderate volatility through various drivers such as utility on a platform, burning mechanisms, and episodic regulatory focus. XRP's price action is somewhat tame but shows episodic spikes tied to legal events, specifically related to its current litigation against U.S. regulators.

On the other hand, Tether exhibits near-permanent pricing, consistent with its nature as a fiat-pegged stable coin secured by U.S. dollar reserves. The lack of sharp fluctuations in its price reflects its key function as a stable medium of exchange and a liquidity-maintaining instrument. On a returns basis, disparities are even more acute. Bitcoin and Ethereum returns are highly volatile, with steep reversals and outlier values characteristic of systemic and idiosyncratic volatility. Returns are leptokurtic for them, indicative of fat-tailed behavior. BNB and XRP also display substantial, albeit relatively less severe, return volatility. These assets almost certainly have non-normal return distributions with fewer outlier deviations than BTC and ETH. Tether returns are tightly clustered near zero, consistent with its non-speculative nature and stability in price. Together, these results highlight differentiated roles, volatility regimes, and return properties unique to each digital asset. Regulators and investors must identify divergence between assets designed toward transactional stability (e.g., TETH) versus those subject to speculative value dynamics (e.g., BTC, ETH). This structural heterogeneity has particular consequences for asset allocation, regulatory architectures, and overall integration of cryptocurrencies into mainstream finance.

Table 1 shows the descriptive statistics highlighting key return behaviors of major cryptocurrencies. BNB showed the highest average daily return (0.1615%), which translates to an approximate annualized return of about 40% (assuming simple compounding over 252 trading days). Tether had a slight negative daily return (-0.00038%), which is roughly -0.1% annualized. BTC and ETH posted moderate daily returns (0.0772% and 0.0457%), corresponding to approximate annualized returns of about 20% and 12%, respectively. XRP exhibited the most significant volatility (SD = 5.5314), followed by BNB (5.0091), with Tether the least volatile (0.2163). All except BNB displayed significant skewness, negative for BTC (-1.108***) and ETH (-0.983***), indicating frequent extreme losses, and positive for Tether and XRP. Excess kurtosis values confirmed fat tails, especially for Tether (39.476***), suggesting rare, large price shifts. Significant Jarque-Bera statistics confirmed non-normal return distributions. Q and Q- tests indicated serial correlation and volatility clustering, particularly in Tether. These results underscore the complexity and risk inherent in cryptocurrency markets.

The Spearman correlation matrix, derived from the daily returns of five significant cryptocurrencies over the entire sample period, is also shown in Table 1. According to the findings, there is a definite and substantial positive correlation between Bitcoin and both ETH (0.811) and BNB (0.675). This means that these assets tend to move in tandem, even when normal market volatility is factored in. In contrast, XRP exhibits a moderately positive correlation with both Bitcoin (0.606) and Ethereum (0.650), which suggests that broader market forces likely influence all three. On the other hand, Tether (TETH) stands out for its weak and even slightly negative correlations with the rest (for instance, -0.108 with BTC). That makes sense, though—Tether is a stablecoin, so it is often used as a safe haven or a tool for managing liquidity when the market gets rocky.

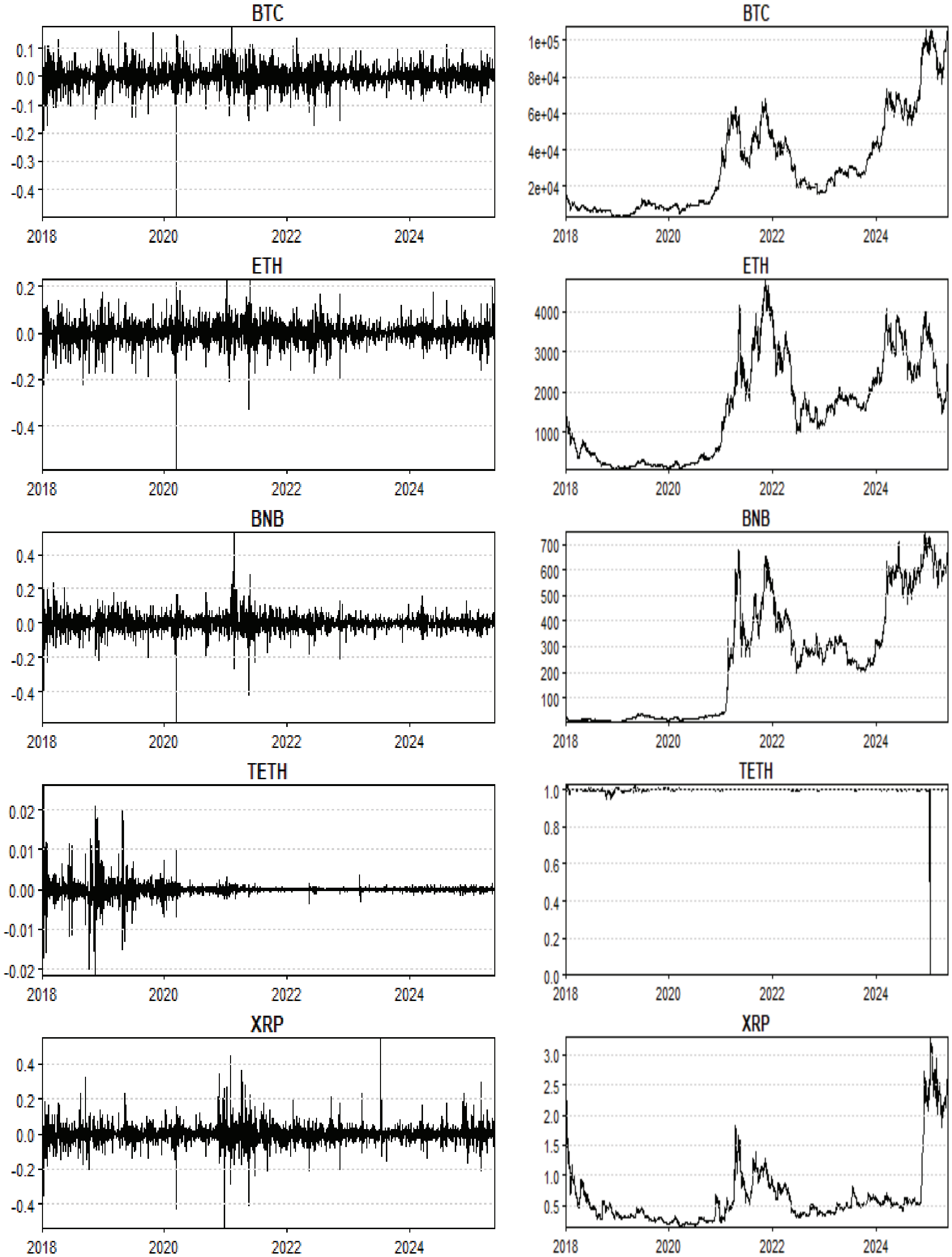


Fig. 1. Dynamics of prices and returns

Panel A: Basic Statistics

	BTC	ETH	BNB	TETH	XRP
Mean	0.0772	0.0457	0.1615	-0.00038	0.0055
Median	0.0534	0.0773	0.108	0	0.0272
Maximum	17.7424	23.0772	53.0574	2.6165	54.8118
Minimum	-49.7278	-58.9639	-58.1158	-2.1557	-54.1011
.Std.Dev	3.5727	4.6515	5.0091	0.2163	5.5314
Skewness	***-1.108	***-0.983	0.071	***0.526	***0.439
Ex.Kurto-sis	***16.564	***12.831	***22.226	***39.476	***15.864
JB	***31385.383	***18935.836	***55514.950		
ERS	*** -3.439	*** -3.169	*** -13.717	*** -1.925	*** -7.247
(Q(20	***24.680	***39.942	***31.564	***325.087	14.668
(Q2(20	***52.173	***91.711	***341.456	***1511.955	***135.301

Panel B: Spearman Correlation matrix

	BTC	ETH	BNB	TETH	XRP
BTC	***1.000				
ETH	***0.811	***1.000			
BNB	***0.675	***0.698	***1.000		
TETH	***-0.108	***-0.100	***-0.086	***1.000	
XRP	***0.606	***0.650	***0.544	**-0.044	***1.000

Table 1: Descriptive statistics

5. Empirical results:

We use daily price data for each cryptocurrency from January 1, 2018, to May 20, 2025, resulting in approximately 2,700 observations per series. Wavelet coherence is computed using the Morlet wavelet with a nondimensional frequency parameter (- -) of 6, balancing time and frequency localization. Scales are selected to capture periods from roughly 4 days (high frequency) to 512 days (low frequency), ensuring coverage of short-term trading cycles and long-term investment horizons. We employ a cone of influence to account for edge effects and apply smoothing in both time and scale following Grinsted et al. (2004), using default smoothing constants to mitigate noise without over-smoothing structure. We also conducted sensitivity checks varying - - between 5 and 7, adjusting smoothing levels, and narrowing scale ranges. While minor differences in the exact shape of coherence islands emerged our findings are not artifacts of parameter tuning but reflect genuine time-frequency dependencies in the data.

The wavelet coherence between Bitcoin (BTC) and Ethereum (ETH) reveals a persistently high level of synchronization across almost all time scales, especially from mid-2019 onward. The coherence is strongest in the long-term (scale > 128 days) band, peaking around 2020–2021 and again in 2023–2024, corresponding to major market rallies and regulatory episodes. Arrows pointing to the right and upward suggest BTC and ETH are in-phase, with BTC often leading ETH at lower frequencies. This reflects Ethereum's strong correlation with market-wide trends, likely driven by its dual role as a speculative asset and infrastructure backbone for DeFi and Non-Fungible Tokens (NFTs).

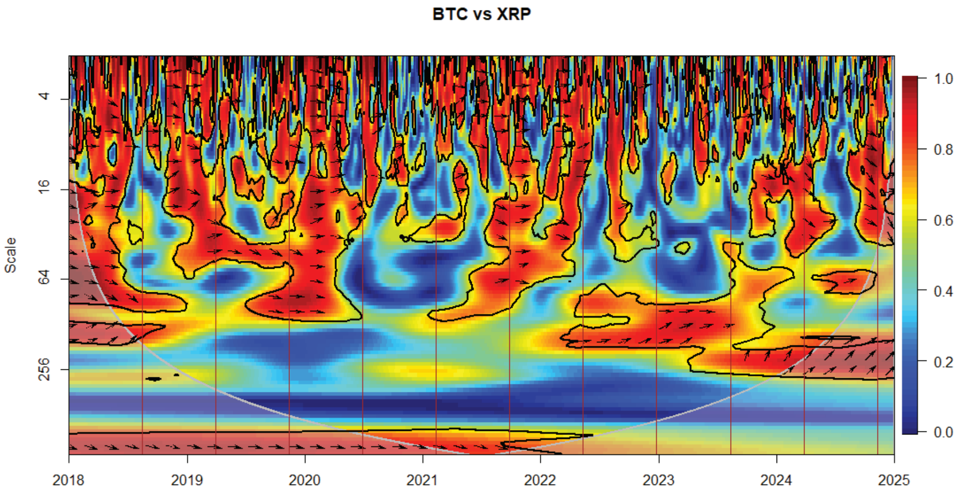
The BTC–BNB relationship exhibits strong coherence across both short-term (4–16 days) and long-term (>128 days) horizons, with particularly pronounced synchronization during the 2020–2022 bull market, an interval marked by the expansion of the Binance Smart Chain and a surge in decentralized finance activity. This heightened coherence suggests that broader market momentum, as well as ecosystem-specific developments, played a significant role in aligning the dynamics of Bitcoin and Binance Coin during this period. However, from late 2022 onward, the coherence between BTC and BNB becomes more intermittent, indicating episodes of decoupling that may be attributable to exchange-specific incidents or heightened regulatory scrutiny facing Binance. Arrows indicate bidirectional influence, with BNB occasionally leading at medium-term frequencies, reflecting exchange-driven liquidity dynamics and cross-market arbitrage flows. In contrast, the co-movement between BTC and Tether (TETH) is more irregular and tends to appear in the medium- to long-term frequency bands (32–256 days). The characteristically low coherence at high frequencies is consistent with Tether's stable price profile. Nevertheless, distinct periods of elevated coherence are observed, particularly in late 2018, early 2020, and late 2022, which align with episodes of market stress and heightened redemption activity. Arrows generally point left or downward, indicating anti-phase movements and inverse liquidity signaling: BTC downturns coincide with increased TETH activity, possibly due to investor retreat into stable assets.

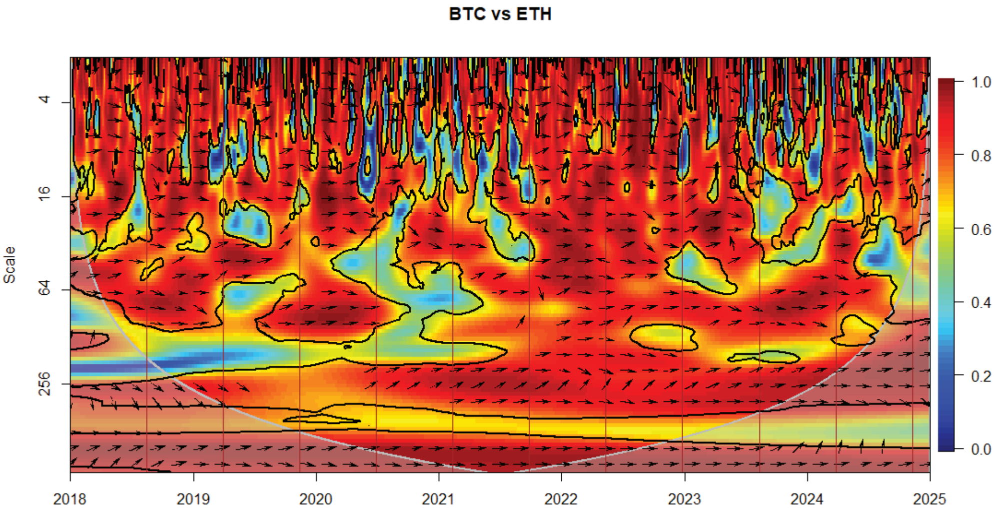
The BTC–XRP pair exhibits moderate coherence with distinct periodic bursts, particularly during late 2019, mid-2021, and late 2023. These align with Ripple's legal developments (e.g., SEC lawsuit) and broader market volatility. Coherence is concentrated in the short-to-medium term (8–64 days) bands. Arrows show mixed phase relationships, with alternating lead-lag structures that imply XRP reacts both to systemic market moves and idiosyncratic events. Compared to ETH and BNB, XRP shows less structural coupling to BTC, reinforcing its more segmented market position.

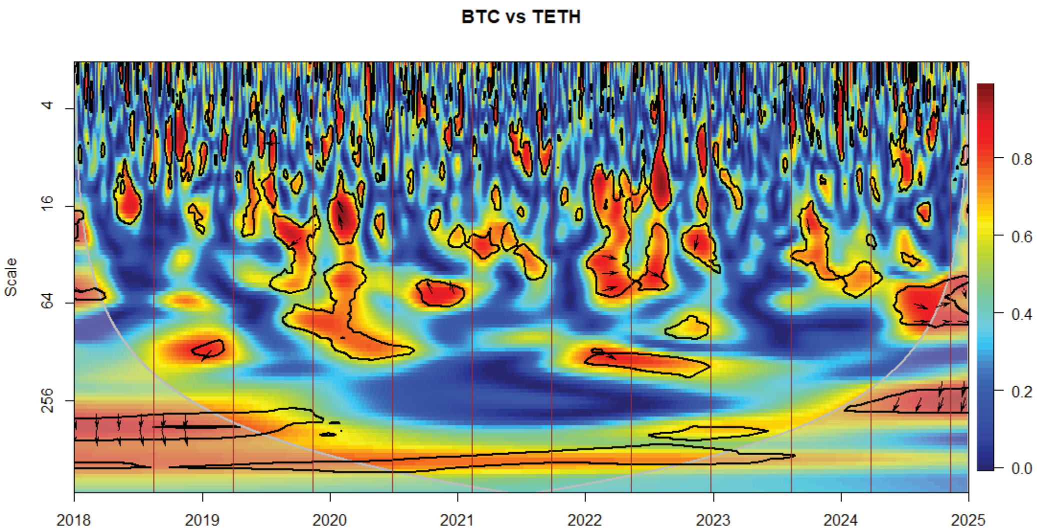
These findings underscore the heterogeneity in co-movement dynamics among top cryptocurrencies. BTC–ETH coherence is structural and persistent, reinforcing their roles as core benchmarks and systemic influencers in crypto markets. BTC–BNB shows strong coherence linked to exchange-driven dynamics and episodic deviations reflecting platform-specific events. BTC–TETH coherence is conditional and counter-cyclical, reflecting the safe-haven role of stablecoins during volatility shocks. BTC–XRP coherence is weaker and event-driven, shaped by regulatory pressures and legal uncertainty rather than macro-crypto trends.

From a portfolio perspective, the high coherence of BTC with ETH and BNB implies limited diversification benefits within these pairs. Conversely, the more fragmented relationships with TETH and XRP suggest potential hedging or stability roles under certain conditions. These results validate the power of wavelet coherence to uncover time- and scale-specific interdependencies that static models overlook. Moreover, the directional coherence analysis (via phase arrows) reveals nuanced lead-lag structures, critical for high-frequency traders, market makers, and algorithmic strategy developers.

From a macroprudential policy perspective, the results of this research can help reduce financial stability threats related to increased correlations among leading cryptocurrencies. Regulatory agencies might consider developing real-time monitoring systems that use time-frequency analytics to identify periods of elevated systemic risk and market synchronization. This data can support targeted strategies, such as countercyclical capital buffers or flexible margin requirements, for entities heavily involved in digital assets. Additionally, macroprudential frameworks could be adapted to include liquidity requirements specific to crypto-asset markets, ensuring that exchanges and other critical intermediaries can withstand shocks and meet obligations during market stress. Finally, scenario analysis and thorough market stress testing can help regulators anticipate and prevent spillover effects before they threaten overall financial stability.






BTC vs TETH
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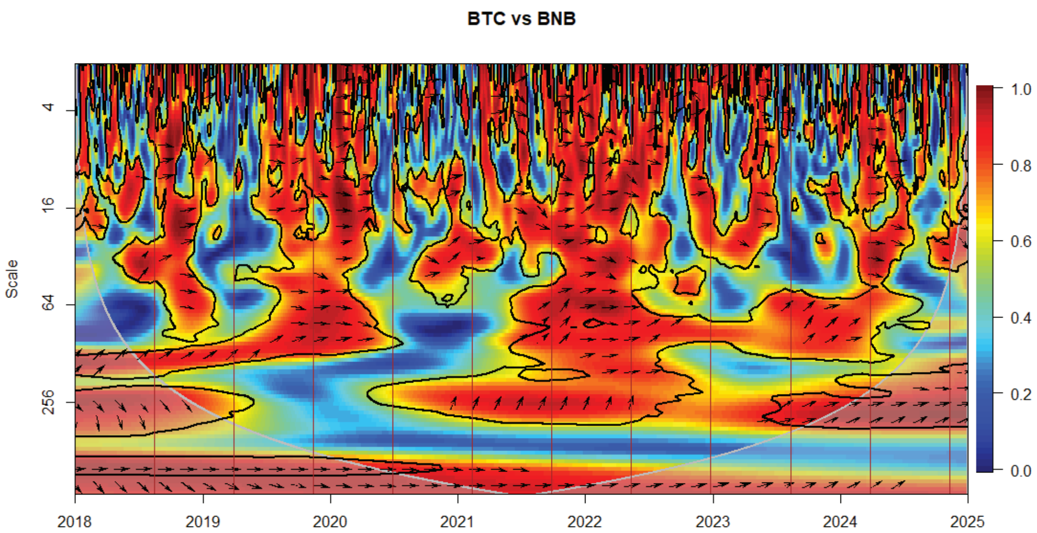
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6. Conclusion:

This study examines the co-movement dynamics among the five leading cryptocurrencies, based on market capitalization, from January 1, 2018, to May 20, 2025: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Tether (USDT), and Ripple (XRP). By applying wavelet coherence analysis within a time-frequency framework, we move beyond traditional linear models to reveal how correlations among these digital assets shift over time and in response to varying market pressures.

The findings provide several new insights. Most notably, the consistent significant coherence between BTC and ETH reaffirms their status as core anchors in the broader crypto-financial system. Their sustained in-phase relationship, which has survived shocks such as the COVID-19 pandemic, geopolitical tensions like the Russia-Ukraine conflict, and economic disruptions like the Trump-era tariffs, suggests a pattern of mutual reinforcement and mutual vulnerability. This interdependence enhances their systemic importance. In contrast, the BTC–BNB dynamic demonstrates strong yet sporadic coherence, often linked to platform-specific developments. This highlights the significant impact of exchange-linked tokens on shaping cross-market behavior. Meanwhile, BTC–TETH interactions generally remain weak but spike during periods of market stress, affirming Tether's stabilizing, counter-cyclical function. Regarding BTC–XRP, their relationship appears more transient and reactionary, primarily influenced by legal rulings and policy updates rather than broader market structures.

Overall, these patterns highlight an important point: co-movements among cryptocurrencies are neither uniform nor constant. They are structurally unbalanced and depend on each asset's economic role, market structure, and institutional environment. This has practical implications. Our analysis offers several key insights for both regulators and market participants in the financial industry. For policymakers, the finding that major cryptocurrencies, such as Bitcoin and Ethereum, exhibit strong and often changing relationships suggests that a one-size-fits-all regulatory approach will not be sufficient. Regulators may need to explore more flexible methods that can keep pace with the rapid changes in the cryptocurrency landscape. For example, using time-frequency analysis could help identify systemic risks early and enable timely interventions. This could include implementing circuit breakers during major market swings or adjusting capital requirements when risk indicators rise. For stablecoins like Tether, which tend to provide stability during market downturns, focus should shift toward tighter transparency standards. This involves increased audit frequency, clearer reserve disclosures, and stricter regulations to ensure these coins are reliable. If regulators handle this effectively, it could greatly enhance protections for the broader market against unforeseen shocks.

From the perspective of banks and asset managers, our results highlight a significant concern: that diversifying investments across leading cryptocurrencies to mitigate risk may be flawed, especially when these assets begin to move in tandem. Therefore, it is wise for portfolio managers to regularly update their strategies, ideally using methods that monitor how these connections change, such as wavelet coherence analysis. Sometimes, this means focusing on assets that diverge from current trends, such as certain stablecoins or tokens not tied to major entities. Some cryptocurrencies tend to lead and influence others, which traders can potentially leverage. Overall, consistent stress testing and scenario analysis are vital for maintaining strong portfolios. In a rapidly changing environment, staying flexible is essential.

Although this paper presents novel findings of time–frequency co-movement relationships between leading cryptocurrencies, it suffers from several limitations. Firstly, our comparison is confined to the five top cryptocurrencies by market capitalization and may overlook relevant co-movements between smaller or emerging tokens. Secondly, we employ daily closing rates, which might overlook intra-daily volatilities and high-speed trading behavior that could dictate short-run coherence. Thirdly, whereas the wavelet coherence technique is robust in exhibiting time–frequency dependences, it does not explicitly model causality or structural breaks, albeit qualitatively through phase analysis. Fourthly, our method assumes stationarity in localized time–frequency intervals and is prone to extreme market realizations or regime shifts not comprehensively captured in such analysis. Lastly, the findings are subject to the sample period, wavelet parameters, and test of significance, which, despite our checks for dependence, might not universally generalize to all market regimes.

Looking ahead, Future research could re-estimate the key models using different parameter values and alternative smoothing techniques and complement our time–frequency wavelet approach with Granger causality tests and Information Sharing models (Hasbrouck, 1995; Grammig & Peter, 2013), ideally using high-frequency intraday data, to provide more precise insights into lead–lag relationships and price discovery contributions among cryptocurrencies. Incorporating macroeconomic and microeconomic factors, such as interest rate variations, supply and demand, and inflation, as well as unanticipated monetary policy changes, may help shed light on how external influences affect the co-movements of cryptocurrency. Furthermore, examining the impact of investor sentiment, geopolitical concerns, and increased institutional involvement can help us better understand the drivers of coherence patterns. More advanced approaches, such as multivariate wavelet coherence or hybrid models that include machine learning, could also be helpful in future studies to identify probable regime transitions or systemic weaknesses. Ultimately, this study makes a significant contribution to cryptocurrency research by elucidating the fluid and context-dependent nature of co-movement structures among the five digital assets, based on market capitalization.

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