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REVISITING THE DYNAMICS OF MAJOR CRYPTOCURRENCIES

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Abstract. *Purpose* – This study aims to reassess the dynamics of major cryptocurrencies surrounding recent economic and geopolitical events. By employing wavelet analysis and quantile regression methods, it seeks to understand the behavior of cryptocurrencies before, during, and after the COVID-19 pandemic.

Research methodology – This research employs the Least Asymmetric Daubechies (LA8) wavelet function to decompose log-returns of major cryptocurrencies into various frequency scales. Additionally, it utilizes wavelet coherence and quantile-on-quantile regression techniques to analyze daily price data spanning from July 2017 to May 2024.

Findings – The findings reveal a strong long-term association among cryptocurrencies, with a decline in medium-term correlations. Bitcoin exhibits synchronization with major cryptocurrencies, excluding Tether, while BTC-ETH and BTC-BNB display a rapid, interconnected behavior alongside their fundamental links. Moreover, empirical evidence indicates Bitcoin's heterogeneous nexus with other alternatives, showcasing greater sensitivity to positive extremes over negative ones.

Research limitations – The study's scope is delimited by the selected time frame (July 2017 to May 2024) for data analysis, potentially limiting insights into longer-term trends. Additionally, the reliance on specific methodologies like wavelet analysis might introduce constraints in capturing the entirety of cryptocurrency dynamics, leaving room for alternative interpretations or unexplored aspects.

Practical implications – Results suggest that understanding the varying correlations among major cryptocurrencies during different market phases could aid investors and policymakers in devising more nuanced strategies. Recognizing the sensitivity of Bitcoin's connections with alternatives to market trends could inform risk management approaches, particularly in navigating extreme market conditions.

Originality/Value – The originality of this study lies in its comprehensive examination of cryptocurrency dynamics across varying time scales, utilizing wavelet analysis and quantile regression techniques. The findings offer valuable insights into the complex interconnections among cryptocurrencies, especially in terms of their sensitivity to different market conditions, providing a nuanced perspective for investors, analysts, and policymakers navigating the crypto landscape.

Keywords: Bitcoin, Ethereum, cryptocurrencies, wavelets, co-movement.

JEL Classification: G10, G12, G14, G40.

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1. Introduction

Since Bitcoin was introduced in 2008, cryptocurrencies have fascinated both investors and researchers. Born out of the 2008 global financial crisis, these digital assets have seen substantial growth, providing an attractive alternative to traditional investments. The popularity of cryptocurrencies like Bitcoin and Ethereum has surged, indicating a broader trend towards alternative assets among investors. Gulseven and Ekici (2016) noted that the global financial crisis led investors to seek new opportunities, with cryptocurrencies fitting that need for many. Research by Corbet et al. (2019), Balli et al. (2020), and Arif et al. (2021) underscores the potential of cryptocurrencies as alternatives to traditional investments.

Cryptocurrencies have become a notable part of global financial markets, widely used in online transactions and drawing global attention, as highlighted by Juškaitė and Gudelytė-Žilinskienė (2022). Financial markets have a history of crises. The COVID-19 pandemic is the latest disruption, affecting markets worldwide (Bai et al., 2020; Luu & Luong, 2020; Abuzayed & Al-Fayoumi, 2021; Le & Tran, 2021; Umar et al., 2021; Nurdany et al., 2021). While the pandemic may have challenged the role of cryptocurrencies as a diversification tool (Hung, 2021), understanding their interconnectedness could reveal new investment opportunities.

The rapid growth and volatility of the cryptocurrency market can lead to financial instability but may also act as a safeguard during crises like COVID-19 (Demir et al., 2020). Zhang et al. (2020) highlight the instability caused by this volatility, while López-Martín et al. (2021) discuss market inefficiencies and the gradual improvement in market efficiency. Understanding the relationships between cryptocurrencies is crucial for smart investment, risk management, and financial stability. Researchers use various econometric methods to study the cryptocurrency market. Almansour et al. (2020) used ARMA, ARCH, and GARCH models to predict bitcoin returns and analyze exchange rate effects. Tapia and Kristjanpoller (2022) applied Long-Short Term Memory models to predict bitcoin volatility effectively. Omane-Adjepong et al. (2019) used wavelet analysis to examine the connections between seven cryptocurrencies, finding these connections are influenced by trading scales and market volatility. These studies illustrate the diverse methods used to understand financial market interactions, including causality tests, co-integration, structural vector auto-regression, and more.

Building on this literature, our research employs the wavelet approach to visualize the dynamic, time-varying relationships in both time and frequency domains. By using wavelet coherence, we aim to understand the physical interactions between time series and the synchronization behavior of Bitcoin compared to other major cryptocurrencies. The study extends the analysis through multiresolution decomposition (MRD) to compare long-run business cycles and quantile-on-quantile regression to assess the impact of market booms and crashes. This approach will help determine whether Bitcoin's relationships with other cryptocurrencies have been homogeneous or heterogeneous across different market conditions.

This study is crucial for investors and portfolio managers in the cryptocurrency market as it seeks to understand the co-movement dynamics and causal relationships among cryptocurrencies across different time-frequency spaces. From the perspective of investment theory, it aims to explore the timing effect of the diversification principle proposed by Markowitz (1952), which suggests that diversification benefits arise when asset allocation is based on low or negative correlations among assets. Understanding these dynamics can help in making informed investment decisions and optimizing portfolio performance. Additionally, the study addresses the Financial Crises Theory by investigating the "extreme manifestations" (Claessens & Kose, 2013) of interactions within the cryptocurrency market and their connection to economic events.

Our research aims to answer several critical questions about the cryptocurrency market. We first investigate whether the empirical co-movement among cryptocurrencies is predominantly a long-run, medium-run, or short-run relationship, and how it evolves over time and across different frequencies. Next, we also examine how recent crises, such as the COVID-19 pandemic, have impacted the dynamics of these relationships and the overall dependence structure among cryptocurrencies during crises. Finally, by exploring these aspects, our study intends to provide deeper insights into the resilience and interdependencies within the cryptocurrency market, particularly in the context of financial turmoil. This research will offer valuable information for investors, policymakers, and researchers interested in the stability and dynamics of digital asset markets.

2. Literature review

In a recent study, Li et al. (2021) explored the relationship between investor attention and major cryptocurrency markets using wavelet-based quantile Granger causality. Their analysis revealed a complex interplay between investor attention and cryptocurrency returns. They found a bidirectional causality between investor attention and the returns of Bitcoin, Ethereum, Ripple, and Litecoin across various quantiles, except for the medium range. However, the impact of investor attention on Ethereum returns was relatively weak. The study noted that in the short term, the causality appeared symmetrical, but it became asymmetrical in the medium and long term, with investor attention having a stronger influence on cryptocurrency returns during bearish markets compared to bullish ones.

Umar et al. (2021) examined the connectedness between the technology sector and cryptocurrency markets using Diebold and Yilmaz's (2012) connectedness approach from 2012. They discovered that the cryptocurrency market is less integrated with the tech sector and less exposed to systemic risk. Earlier, Fruehwirt et al. (2020) used wavelet coherence analysis to study the dynamic relationships between different cryptocurrencies, noting increasing interdependence and instability. Fidrmuc et al. (2020) also used wavelet coherence to examine Bitcoin, Ethereum, and Litecoin from 2013 to 2019, suggesting that phase shifts among these cryptocurrencies could indicate trends for various investment horizons. Similarly, Kang et al. (2019) found strong coherence between Bitcoin and future gold prices, especially over 8 to 16-week periods. Studies also emerged questioning whether cryptocurrencies could serve as better safe-haven assets than the US dollar and gold, or as hedgers or diversifiers in investment portfolios (Bouri et al., 2017; Fang et al., 2019; Wang et al., 2021; Maitra et al., 2022; Xu & Kinkyo, 2023).

Kumah and Odei-Mensah (2022) explored the asymmetric transmission of shocks between seven major cryptocurrencies and crude oil under different market conditions using the wavelet technique. This method decomposed the daily return series of these assets into various wavelet scales to identify different trading horizons. The study applied quantile regression (QR) and quantile-in-quantile regression (QQR) to the decomposed series, capturing bear and bull market conditions. QR results indicated that Ethereum, Stellar, Ripple, and Monero effectively hedged against volatility in the oil market across medium to long-term regimes. In contrast, Bitcoin, Litecoin, and Dash showed weakened hedging properties, suggesting potential market disruptions from these cryptocurrencies to the crude oil market. The QQR analysis further demonstrated a negative influence among the assets during bear markets but a positive influence during bull markets over time, highlighting potential hedging opportunities during bear markets.

Additionally, Kumah and Mensah (2022) investigated the relationship between seven cryptocurrencies and gold during bear and bull markets to identify the hedging properties of cryptocurrencies for gold investors. Using the wavelet technique, they decomposed daily return series into short-term, medium-term, and long-term frequencies and applied QR and QQR across 19 quantiles. QR results showed that all cryptocurrencies served as hedges for gold in the medium to long term, regardless of the market regime. However, QQR results revealed an inverse association between the assets during bear markets and a positive association during bull markets over time, suggesting hedging opportunities in bear markets. Similarly, Umar et al. (2023) examined the influence of economic policy uncertainty (EPU) on the returns of 100 highly capitalized cryptocurrencies from January 2016 to May 2021, using panel data analysis and quantile regression. They found that increases in global EPU positively impacted cryptocurrency returns at lower quantiles while adversely affecting upper quantiles. The COVID-19 pandemic further strengthened the relationship between EPU and cryptocurrency returns, with cryptocurrencies behaving more like traditional financial assets post-pandemic.

Trucíos and Taylor (2023) explored various methods for predicting daily risk measures in cryptocurrency markets, including long-memory processes, extreme observation accounting, multiple regime models, and quantile regression-based approaches. Their study reevaluated these methods' effectiveness in forecasting value at risk and expected shortfall using recent Bitcoin and Ethereum data, which covered turbulent market periods like the COVID-19 pandemic, Bitcoin's third halving, and the Lexia class action. They also examined forecast-combining strategies to address potential model misspecification and enhance accuracy. Extensive back-testing revealed that for Bitcoin, no single method consistently outperformed others, while for Ethereum, the GAS model proved effective for both risk measures. Notably, the combining methods could not surpass the performance of individual models.

Apergis (2023) analyzed dynamic spillover effects in the cryptocurrency market using 1-minute data from nine cryptocurrencies between 2017 and 2021. The Time-Varying Parameter Vector Autoregression (TVP-VAR) approach showed that spillover effects intensified during shocks like the COVID-19 pandemic. The study highlighted that higher-order moment spillovers provided additional insights beyond return and realized volatility spillovers. Different cryptocurrencies acted as either senders or recipients of spillovers, influenced by various factors within the market and the pandemic's impact. Similarly, Khalfaoui et al. (2023) examined the effects of COVID-19-related panic, stress, and uncertainties on the volatilities of three green bond markets using daily data from January 2020 to January 2022. Their combined TVP-VAR and quantile regression analysis revealed significant information spillovers during bearish conditions, with MSCI Euro green bonds as primary shock recipients and fake COVID-19 news as major shock contributors, followed by Bitcoin.

3. Methodology

We first collect and update the data for specific cryptocurrencies based on their market valuation. To avoid econometric issues calculate the log-returns based on difference of the logs. Next, we follow two unique approaches to analyze the relationship between Bitcoin and other cryptocurrencies.

Our first approach is the wavelet decomposition. Wavelet decomposition is a powerful tool for analyzing time series data, allowing the decomposition of a time series into various resolution levels using wavelets. Wavelets are specialized mathematical functions that can capture both high frequencies occurring over short time scales and low frequencies occurring over long time scales. This type of analysis is known as multiresolution decomposition (MRD), where each resolution level corresponds to a different time scale.

The wavelet decomposition process is founded on the principles of Fourier transform and series analysis, which traditionally rely on sine and cosine functions to represent the frequencies within a time series. However, while Fourier analysis captures the frequency components of a time series as a whole, wavelet analysis provides the ability to decompose the time series into its frequency components at different time scales. This is particularly useful for analyzing non-stationary signals where the frequency characteristics can change over time. Mathematically, the wavelet decomposition of a time series $f(x)$ can be represented by the following Equation (1):

$$f(x) = \sum_k s_{j,k}\phi_{j,k}(x) + \sum_k d_{j,k}\phi_{j,k}(x) + \sum_k d_{j-1,k}\psi_{j-1,k}(x) + \cdots + \sum_k d_{1,k}\psi_{1,k}(x), \tag{1}$$

where $\phi(x)$ and $\psi(x)$ are the father and mother wavelet functions, respectively. In wavelet decomposition, the father wavelet (often referred to as the scaling function) represents the smooth component approximation of the time series, while the mother wavelet is used to capture the detail components of the time series. The decomposition process involves calculating smooth coefficients where $s_{j,k}$ are the smooth coefficients and $d_{j.k}...d_{1,k}$ are the detail coefficients, where j and k are the scaling and translation parameters, obtained from the wavelet transform. In that respect, the general representation of the time series $f(x)$ decomposition in terms of its detailed D_J and smooth series S_J, is given as in Equation (2),

$$f(x) = S_J + \sum_{j=1}^{J} D_j = S_J(x) + D_J(x) + D_{J-1}(x) + \cdots + D_1(x), \tag{2}$$

where: S_j represents the smooth coefficients at scale j (obtained using the father wavelet), and D_j represents the detail coefficients at each scale j from 1 to J (obtained using the mother wavelet).

The smooth coefficients $s_{j,k}$ and the detail coefficients $d_{j,k}$ are derived from the wavelet transform and provide a complete representation of the time series $f(x)$ at different levels of detail. Based on Daubechies (1988) functions, the father and mother wavelets can be represented in their discretized forms. Let's denote the father wavelet as $\phi(x)$ and the mother wavelet as $\psi(x)$. These discretized wavelets are used in the wavelet transform to decompose a time series into its smooth and detail components, enabling multi-resolution analysis. Based on Daubechies (1988) functions, Equations (3) and (4) represent the father $\phi(x)$ and mother $\psi(x)$ wavelets discretized versions,

$$\phi(x) = \sum_k h_k \phi(2x - k); \tag{3}$$

$$\psi(x) = \sum_k g_k \phi(2x - k). \tag{4}$$

The scaling and wavelet coefficients are crucial for constructing the wavelets and are defined for each type of Daubechies wavelet. The specific values of these functions depend on the order of the Daubechies wavelet.

The analysis of interconnections among time series transformed to log-returns can be effectively performed using wavelet correlation and coherence. The Maximal Overlap Discrete Wavelet Transform (MODWT) is particularly useful for this purpose as it allows for scale-based additive decomposition of the time series *f*(*x*) while maintaining the length of the wavelet coefficients equal to that of the original time series. In this context, using the Least Asymmetric Daubechies LA (8) function as the mother wavelet, the wavelet unbiased correlation estimator is performed as shown in Equation (5),

$$\tilde{\rho}_{X,Y}(\lambda_j) = \frac{\gamma_{X,Y}(\lambda_j)}{\nu_X(\lambda_j)\nu_Y(\lambda_j)}, \tag{5}$$

where $\gamma_{X,Y}$ is the covariance between time series X and Y at scale λ_j, ν_X^2 and ν_Y^2 are the variances of X and Y, respectively, at scale λ_j. In wavelet analysis, the parameter $\lambda_j = 2^{j-1}$ represents the timeframe associated with the j–th scale. This parameter is crucial for understanding the temporal resolution of the wavelet-transformed data at different scales. If the original data is sampled daily, the 1-scale corresponds to a 1-day window. The decomposed correlation at this scale captures interactions that occur within a 1-day period. At the 2-scale, the wavelet correlation captures interactions over a 2-day window. At the 3-scale, the interactions are captured over a 4-day window. For a general J-level, the timeframe extends to 2^{J-1} days. Using this interpretation, wavelet correlation at different scales allows for the analysis of interactions between time series data over varying time windows. This multi-resolution approach is particularly useful in financial time series, where relationships between variables may change over different time horizons.

We employed the bivariate wavelet coherence method for examining the time-varying association between two cryptocurrency time series. This method allows for the comparison of the frequency contents of these time series, providing insights into their synchronization over specified periods and across specific time ranges. (Torrence & Compo, 1998; Torrence & Webster, 1999; Grinsted et al., 2004). Wavelet coherence is computed using the cross-wavelet transform, which extends the wavelet transform to analyze the relationship between two time series in both time and frequency domains. Its is analogous to the correlation coefficient but in the time-frequency domain. It can be represented mathematically as in Equation (6):

$$W_{XY}(s,t) = \frac{\left|W_X(s,t)W_Y^*(s,t)\right|}{\left|W_X(s,t)\right|\left|W_Y(s,t)\right|}, \tag{6}$$

where:

- $W_X(s,t)$ and $W_Y(s,t)$ are the wavelet transforms of the time series X and Y at scale s and time t, respectively;

- $W_Y^*\left(s,t\right)$) is the complex conjugate of $W_Y(s,t)$;
- The numerator $\left|W_X\left(s,t\right)W_Y^*\left(s,t\right)\right|$ represents the cross-wavelet power;
- The denominator $\left|W_X\left(s,t\right)\right|\left|W_Y\left(s,t\right)\right|$ normalizes the coherence measure.

The wavelet coherence $W_{XY}(s,t)$ ranges from 0 to 1, where 0 indicates no coherence (no correlation) and 1 indicates perfect coherence (perfect correlation) between the two time series at a particular scale and time.

Wavelet coherence graphs visually represent the coherence between two time series across different scales and times. These graphs are useful for identifying regions where the time series exhibit strong or weak coherence. In the wavelet graphs, the x-axis represents the time dimension and the y-axis represents the scale or frequency dimension. The coherence values are color-coded, with higher coherence values often represented by warmer colors (e.g., red) and lower coherence values by cooler colors (e.g., blue).

Like correlation, coherence values range from 0 (no coherence) to 1 (maximum coherence). However, instead of providing a single summary statistic, coherency graphs offer a detailed visualization of the relationship over time and across different frequency bands. The legend on the right side of the coherency graph typically displays a color scale. This scale is analogous to the 0 to 1 coherence range, helping interpret the strength of the relationship visually. Regions with colors ranging from blue to green indicate periods and frequencies where the two time series do not exhibit a strong relationship. Regions with colors ranging from yellow to red indicate periods and frequencies where the two time series show a strong relationship.

Figure 1 visualizes the role of arrows in the coherence graphs to provide additional insights into the phase dynamics and lead-lag relationships between two time series. These arrows help interpret how the series are related over time and frequency. Arrows pointing to the right (→) indicate that the variables are in phase, meaning they move together. Conversely, arrows pointing to the left (←) signify that the variables are out of phase, moving in opposite directions.

Regarding phase dynamics and lead-lag relationships, arrows pointing northeast (↗) or southwest (↙) suggest that the first variable is leading the second variable. On the other hand, arrows pointing northwest (↖) or southeast (↘) indicate that the second variable is leading the first variable. This directional information enhances the understanding of the interactions

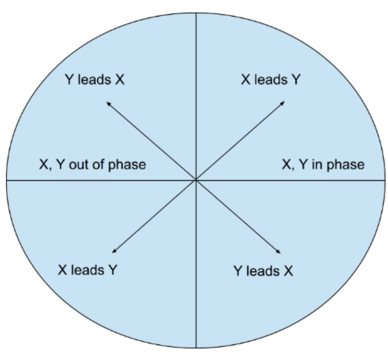

Figure 1. Lead-lag relationship and phase dynamics of variable X against variable Y

between the time series, showing not only the strength of their relationship but also the timing and directionality of their movements.

On the other hand, the nexus and asymmetric effects of a dependent variable against a single or multiple variables (Huo et al., 2022; Ge, 2023) have been modeled using the quantile-on-quantile regression approach (QQR). This method captures the relationship between different quantiles of the dependent variable and the independent variables, providing a nuanced view of their interactions across the distribution. Following Hung (2023), Equation (7) represents the QQR model:

$$Q_{Y|\tau} = \alpha\left(\tau\right) + \beta\left(\tau\right) Q_{X|\tau} + \epsilon_{\tau}, \tag{7}$$

where:

- $Q_{Y|\tau}$ represents the τ-th quantile of the dependent variable *YY*;
- $\alpha(\tau)$ and $\beta(\tau)$ are the quantile-specific intercept and slope, respectively;
- $Q_{X|\tau}$ represents the τ-th quantile of the independent variable *XX*;
- ϵ_{τ} is the error term at the τ-th quantile.

The QQR model provides a comprehensive framework to explore how the relationship between variables changes across different points in their distributions, highlighting the asymmetric effects and dependencies that may not be apparent from traditional regression techniques.

As established by Sim and Zhou (2015), a first-order Taylor expansion of allows for studying the relationship between the θ-quantile of *Y* and the τ-quantile of *X*. Equation (7) can thus be generalized as shown in Equation (8):

$$Y_t = \beta_0\left(\theta, \tau\right) + \beta_1\left(\theta, \tau\right)\left(X_t - X^{\tau}\right) + \varepsilon_t^{\theta}, \tag{8}$$

where:

- Y_t is the value of the dependent variable *Y* at time *t*;
- $\beta_0(\theta,\tau)$ is the intercept term that can vary with both the quantile θ of the dependent variable *Y* and the quantile τ of the independent variable *X*. It captures the baseline level of *Y* when *X* is at its τ-th quantile;
- $\beta_1(\theta,\tau)$ is the slope coefficient that varies with the quantiles θ and τ. It measures the effect of deviations in X_t from its τ-th quantile (X_t) on the θ-quantile of *Y*;
- $(X_t - X^{\tau})$ represents the deviation of the value of X_t at time *t* from its τ-th quantile (X^{τ}); It captures how much X_t differs from the specified quantile value of *X*.

In this context, while Linear Regression based on Ordinary Least Squares (OLS) measures the sensitivity of the dependent variable around its mean in response to the regressors, Quantile Regression provides insights into the responses at different quantiles. This method can capture relationships in the left and right tails of the distribution, revealing connections that might be missed by OLS. As Sim and Zhou (2015) mentioned, the Quantile-on-Quantile (QQ) approach is an extension of Quantile Regression that examines different quantiles of the independent variable. Unlike OLS regression, which measures the effects of the explanatory variable on the conditional mean of the dependent variable, the QQ approach decomposes the effects of the explanatory variable's conditional quantile on the dependent variable's conditional quantile. This allows for a more detailed analysis of how the relationship between variables varies across their entire distributions, providing a richer understanding of their interaction dynamics.

4. Data

The study examines daily data from July 2017 to May 2024 for Bitcoin (BTC), Ethereum (ETH), USDT, Binance Coin (BNB), Ripple (XRP), and Litecoin (LTC), chosen based on their market capitalization and the availability of historical prices from Coin Market Cap (2024). Using daily data allows for the capture of positive and negative extreme returns, providing a higher resolution view of price movements and enabling the detection of large price swings that may be missed with weekly data. This granularity is essential for understanding the high volatility and frequent significant price changes in the cryptocurrency market. Cryptocurrencies were selected based on the most recent market capitalization. While LTC is not among the top-5 cryptocurrencies we also included it in our analysis, as it has been standing for a very long time and is running on a code similar to that of BTC.

Table 1 shows market capitalization as of May 2024, where the top 5 major digital currencies have been Bitcoin, Ethereum, Tether, BNB, and SOL. We decided not to include Solana in our analysis as it is very new with limited historical prices. Instead, despite Litecoin (LTC) standing in the 19th position as a mid-cap cryptocurrency, it holds the distinction of having longer historical price data than many other high-cap cryptocurrencies in this study. Therefore, it is also included in our analysis.

Table 1. Market capitalization of biggest cryptocurrencies (in billion U.S. dollars) (source: CoinMarketCap, 2024)

Name	First Issued	Crypto category	Market capitalization	Notes
Bitcoin (BTC)	July 2010	Store of value	1,400.5	Pioneering cyrptocurrency
Ethereum (ETH)	Aug 2015	Smart contracts	453.5	Cost efficient alternative
USDT	Octr 2014	Stablecoin	111.3	Indexed to 1 USD
BNB (BNB)	July 2017	Exchange token	91.2	Binance exchange token
Solana (SOL)	Apr 2020	Smart contract	80.8	Low transaction cost
USD (USDC)	Sep 2018	Stablecoin	33.2	Regulated in various states
XRP (XRP)	June 2012	Payments	29.9	Cross-border payment
Dogecoin (DOGE)	Dec 2013	Memecoin	23.8	Started as a joke
Toncoin (TON)	Oct 2019	Smart contracts	22.5	Initiated by Telegram
Cardano (ADA)	Oct 2017	Smart contracts	17.8	Uses scientific approach
Litecoin (LTC)	Oct 2011	Payments	6.64	Uses same code as BTC

Original values were transformed to log-returns as specified in Equation (9):

$$\mathrm{Re}\,t_t = \log\left(\frac{P_t}{P_{t-1}}\right), \tag{9}$$

where P_t and P_{t-1} are current and previous prices, respectively.

This transformation is used to normalize the data, making it easier to analyze and compare the returns of different cryptocurrencies over time. Log-returns are particularly useful in financial studies because they provide a time-additive measure of returns, simplifying the calculation of cumulative returns and enabling better modeling of price dynamics and volatility.

Figure 2 shows the combined graphs of prices and log-returns of BTC, ETH, USDT, BNB, XRP, and LTC. By the end of 2017, most cryptocurrencies (except USDT) reached record highs since their initial listings, marking the first significant boom in the cryptocurrency market. However, at the beginning of the following year, the market experienced a sharp decline, with prices dropping to 2019 levels, similar to those seen before the 2017 surge. This decline was primarily driven by three factors: the introduction of Bitcoin futures contracts on the Chicago Mercantile Exchange, government bans on cryptocurrency exchanges, and negative investor sentiment due to the perception of a market bubble without fundamental support for the extraordinary price increases (Cross et al., 2021; Akyildirim et al., 2021).

In early 2019, the cryptocurrency market began a new rally, fueled by renewed confidence in the digital transformation revolution. This resurgence was driven not only by the perceived store of value but also by the increasing use of ICOs for smart contracts and payment purposes, with blockchain-based companies raising funds. According to Statista, ICO fundraising peaked at $6.88 billion in Q1 of 2018, with leading blockchain startups like EOS, Telegram, and TaTaTu raising over $5 billion.

The COVID-19 outbreak caused significant declines in both the cryptocurrency and global stock markets. However, a recovery was achieved within three months due to government economic and monetary policies. During Q1 2020, cryptocurrency prices experienced extreme negative changes, more severe than the 2018 bubble burst. "Easy money" policies, such as low interest rates and quantitative easing programs by central banks, fueled this recovery. This period marked a stronger connection between the crypto market and broader economic indicators, as investors shifted between cryptocurrencies, USD, and stocks based on policy announcements (Hsu et al., 2021; Uzonwanne, 2021).

Post-pandemic recovery saw cryptocurrencies like Bitcoin reach new highs, but prices plunged again in Q3 2021 following China's bans on cryptocurrency trading to combat financial crimes and capital flight. A brief rally in early 2022 was cut short by dramatic price falls linked to the Russian-Ukrainian war and inflationary pressures, leading to tighter monetary policies. In Q1 2023, a slight recovery was observed, driven by positive sentiment regarding inflation and economic outlooks in developed countries, though this recovery was not connected to the SVB financial distress.

However, by 2024, the Securities Exchange Commission made a deal with Binance, which is followed by the approval of several major Bitcoin ETFs (Exchange-Traded Funds). This caused a significant rally in crypto asset prices due to several factors. Firstly, it increased accessibility for institutional investors, who might be restricted from directly investing in cryptocurrencies, thereby bringing more capital into the market. The regulatory approval of these ETFs also added a level of legitimacy, boosting confidence among investors. Additionally, ETFs simplify the investment process by eliminating the need for managing private keys or dealing with cryptocurrency exchanges, thus attracting a broader range of investors. The approval generated positive market sentiment and speculative interest, driving up prices through increased demand. The ease of adding Bitcoin ETFs to diversified portfolios further fueled investment. This positive effect on Bitcoin often spills over to other cryptocurrencies, driving up their prices as well. Besides Ethereum, Binance Coin's price also demonstrated substantial growth, especially after the SEC-Binance deal in 2024, reflecting its increasing utility within the Binance ecosystem, including trading fee discounts, staking, and participation in Binance Launchpad events. The sharp price increases are tied to Binance's strategic moves, such as token burns and new product launches. However, the log-returns graph reveals significant volatility, with large spikes during major announcements or market expansions, indicating the high market sensitivity to Binance's operational changes and BNB's utility-driven demand. It seems like BNB is taking its place as a top cryptocurrency next to BTC and ETH.

Other cryptocurrencies such as XRP and LTC followed a somewhat different path than that of BTC, ETH, and BNB. XRP's price graph features a significant peak in early 2018, followed by a prolonged downward trend interspersed with smaller peaks and corrections. XRP's price is heavily influenced by regulatory news, particularly the ongoing legal issues with the SEC, and partnerships with financial institutions aiming to use Ripple's technology for cross-border payments. The log-returns graph highlights high volatility, especially around regulatory developments and partnership announcements. XRP's price movements and volatility reflect

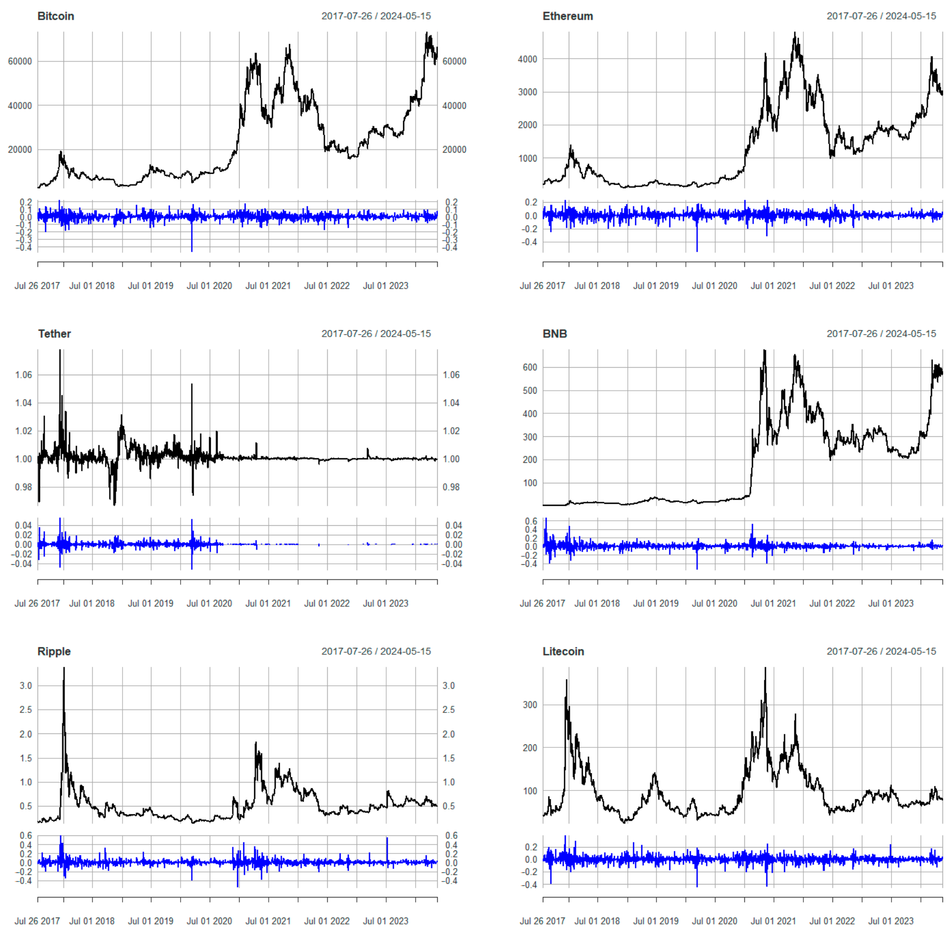

Figure 2. Price and log-returns of Cryptocurrencies

its speculative nature and the market's reaction to legal and adoption-related news. It was also not affected by the SEC-Binance deal.

Similarly, LTC's price graph shows notable peaks in late 2017 and mid-2021, mirroring Bitcoin's price movements but with less intensity. LTC is often considered the "silver" to Bitcoin's "gold," experiencing similar market trends but with its unique fluctuations. The log-returns graph indicates significant volatility, particularly during these peaks, reflecting rapid price changes influenced by market sentiment and broader cryptocurrency trends. Litecoin's behavior was always believed to be a complementary asset to Bitcoin, with its price and volatility patterns often influenced by the same macroeconomic and market factors. However, similar to XRP, it was also not impacted by the SEC-Binance deal.

As expected, Tether's price graph is notably stable, maintaining a close approximation to $1.00, underscoring its role as a stablecoin designed to minimize volatility. Minor deviations from the peg are present but are significantly smaller compared to other cryptocurrencies. The log-returns graph confirms this stability, showing minimal daily percentage changes. Tether's consistency is crucial for its use in trading and as a safe haven during periods of market volatility. It serves as a reliable medium of exchange and a store of value, reflecting its primary function in the cryptocurrency market. Thanks to Binance's P2P system, it is increasingly being used an alternative international remittance transfer mechanism. In many countries it costs at least $30–$40 and takes about 2–3 days to transfer salary to home country. Using Binance P2P system, it takes about 2–3 minutes and maximum $1–$2 to transfer USDT anywhere in the world where Binance operates.

Table 2 provides key statistical metrics for the relevant cryptocurrencies, showing the mean, standard deviation (sd), median, minimum (min), maximum (max), skewness (skew), kurtosis, and the Dickey-Fuller test statistic (D-F). The mean daily returns show that BNB has the highest average gain (0.35%), followed by BTC (0.13%), and ETH (0.11%), while USDT, being a stablecoin, has a near-zero mean return. Standard deviation values indicate that BNB (6.12%) and XRP (5.93%) are the most volatile, while USDT (0.42%) is the least volatile. Median returns are generally close to the mean, except for XRP, which has a negative median (–0.08%). The extreme minimum and maximum daily returns highlight significant fluctuations, with BNB and XRP having the highest single-day gains of 67.52% and 60.69%, respectively.

Skewness values reveal that BTC, ETH, and LTC have negative skewness, indicating a tendency for more extreme negative returns, while USDT, BNB, and XRP have positive skewness,

Table 2. Descriptive statistics of log-returns

Variable	Mean	sd	median	min	max	skew	kurtosis	D-F*
BTC	0.13%	3.81%	0.10%	–46.47%	22.51%	–0.76	12.07	–34.35
ETH	0.11%	4.76%	0.08%	–55.07%	23.47%	–0.91	10.64	–34.32
USDT	0.00%	0.42%	0.00%	–5.26%	5.66%	0.73	51.20	–52.09
BNB	0.35%	6.12%	0.12%	–54.31%	67.52%	1.00	19.10	–31.60
XRP	0.04%	5.93%	–0.08%	–55.05%	60.69%	1.11	19.73	–34.23
LTC	0.03%	5.28%	0.03%	–44.91%	38.93%	–0.21	9.57	–35.17

Note: * Augmented Dickey-Fuller Unit Root Test rejected unit roots at 5% significance.

suggesting more extreme positive returns. High kurtosis values across all cryptocurrencies, particularly USDT (51.20), indicate the presence of heavy tails and a higher likelihood of extreme returns. The Dickey-Fuller test statistics are significantly negative for all cryptocurrencies, suggesting that their return series are stationary. This analysis highlights the high volatility and significant risk associated with cryptocurrencies, contrasted by the stability of USDT, and emphasizes their sensitivity to market conditions and economic policies. The extremeness of USDT is somewhat linked to the prices of major coins. When there is a positive monentum, investors tend to rush into these coins, affectively selling their USDTs, thereby lowering its value. When there is a negativity, investors tend to sell their coins, affectively buying their USDTs, thereby increasing its value. Nevertheless, the deviations are very limited to be maximum –5.26% and 5.66%. This is another interesting point about so-called stable coins.

The heat map in Figure 3 illustrates the correlation coefficients between six cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), USDT, Binance Coin (BNB), Ripple (XRP), and Litecoin (LTC). The color gradient indicates the strength of these correlations, with red shades representing positive correlations and blue shades indicating negative correlations. BTC shows high positive correlations with ETH (0.78), BNB (0.61), XRP (0.54), and LTC (0.74), suggesting that these cryptocurrencies' price movements are closely aligned. Similarly, ETH exhibits strong correlations with BTC (0.78), BNB (0.60), XRP (0.64), and LTC (0.80), indicating that market factors affecting one are likely to influence the others similarly.

USDT, designed as a stablecoin, demonstrates near-zero correlations with all other cryptocurrencies, confirming its role as a stable value asset independent of the volatility in the crypto market. BNB, XRP, and LTC also show moderate to high positive correlations with each other and with BTC and ETH, reinforcing the interconnectedness of these major cryptocurrencies. This correlation pattern highlights that BTC, ETH, BNB, XRP, and LTC tend to move in tandem, driven by similar market forces, while USDT remains largely unaffected by these dynamics.

However, the interaction among cryptocurrencies shown in the Figure 3, as measured by the Pearson correlation coefficient, represents a global correlation which may not capture variations in association levels over different time frames. The wavelet approach addresses this by decomposing the original time series into different frequencies that correspond to

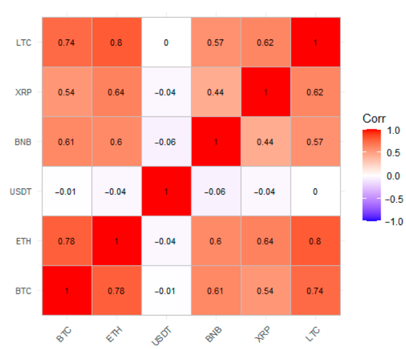

Figure 3. Correlations among cryptocurrencies

various time frames. This method is particularly relevant for investors with different investment horizons, such as short-, medium-, or long-term strategies. While short-term price movements might be volatile, long-term investors may adjust their portfolios gradually as new information emerges, affecting medium- to long-term interactions among assets. This adjustment can distinguish between pure contagion – characterized by rapid and temporary co-movements – and fundamental linkages, which are based on economic fundamentals and persist over time.

Understanding these dynamics is crucial for both active and passive portfolio management. Pure contagion, often described as a "fast and furious" relationship, tends to dissipate quickly, while fundamental linkages reflect deeper economic connections among assets. For portfolio managers, recognizing these different types of co-movement can inform strategies to mitigate risk and optimize returns. By using the wavelet approach, investors can gain insights into how short-term volatility might influence long-term investment decisions, enhancing their ability to manage portfolios effectively across different time horizons.

5. Results and discussion

The wavelet approach we applied here is a powerful method for analyzing the relationship between cryptocurrencies across different time frames by decomposing the original time series into various frequency components. Unlike traditional correlation measures that provide a single global correlation value, the wavelet approach reveals how the strength and nature of correlations vary over time and across different investment horizons. Thus, our method also allows investors to differentiate between short-term, medium-term, and long-term interactions, offering insights into both transient co-movements, often driven by market contagion, and more persistent fundamental linkages based on economic factors. The results of the wavelet analysis that shows how BTC returns are impacted from other major cryptocurrencies is visualized in Figure 4.

Figure 4 shows the dynamic relationship between Bitcoin (BTC) and vs other major cryptocurrencies over time, highlighting how their correlation varies across different frequencies and periods from 2017 to 2024. The x-axis represents the timeline, while the y-axis represents the scale of frequencies, with lower frequencies (longer time periods) at the bottom and higher frequencies (shorter time periods) at the top. The color scale on the right indicates the strength of the coherency, ranging from 0 (no correlation) to 1 (perfect correlation), with red indicating high cohereceny and blue indicating low coherency.

The wavelet coherency graph for Bitcoin (BTC) and Ethereum (ETH) from 2017 to 2023 reveals several distinct patterns. From 2017 to early 2019, there are significant areas of high coherency, particularly at shorter frequencies (top of the graph), indicating that BTC and ETH prices were moving closely together over short-term periods. During this time, market dynamics and investor behavior likely caused synchronized price movements. From 2020 onwards, the coherency varies more, with high coherency observed at both short and long frequencies, suggesting periods where BTC and ETH moved together consistently, especially during major market events. However, there are also patches of low coherency (blue areas), particularly noticeable in mid-2020 and again in late 2022, indicating times when BTC and ETH prices moved more independently during occasional periods. It is clearly observed that since 2021, the coherency between BTC and ETH has significantly increased, indicating a stronger interaction between these two cryptocurrencies over various time frames. This heightened coherency suggests that during periods of crisis, such as market disruptions and economic uncertainties, BTC and ETH tend to move more closely together. The graph shows that during such turbulent times, the interconnectedness of these assets becomes more pronounced, reflecting how crises can amplify the interactions between major cryptocurrencies and lead to more synchronized price movements across different periods. These variations highlight how market events, economic policies, and investor sentiment can differentially impact the coherency between these two leading cryptocurrencies across different time frames.

The wavelet coherency graph for Bitcoin and Binance Coin from 2017 to 2024 shows distinct patterns of interaction across different time frames. Between 2017 and 2019, there are intermittent periods of high coherency at shorter frequencies (top of the graph), indicating strong short-term interactions likely driven by market events and speculative trading. From 2020 onwards, particularly during and after the COVID-19 pandemic, there is an increase in coherency across both short and long frequencies, with pronounced red areas indicating strong coherency during these periods. This suggests that during market upheavals and

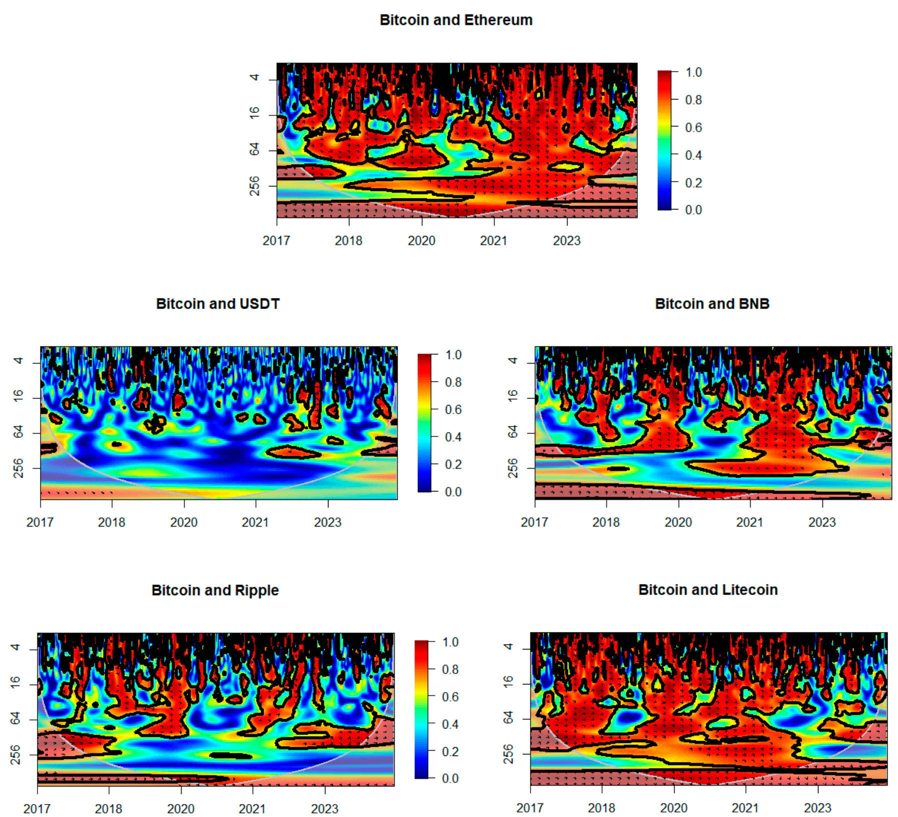

Figure 4. Wavelet analysis for BTC vs other cryptocurrencies

major events, BTC and BNB tend to move together more consistently. Notably, from 2021 to 2024, there is a marked increase in coherency, especially at longer frequencies (bottom of the graph), indicating that BTC and BNB have developed a stronger long-term relationship. This pattern highlights how major market disruptions and economic events can enhance the interaction between these two cryptocurrencies over different time frames.

The analysis for Bitcoin and Ripple also reveals varying degrees of interaction across different frequencies and time frames. Initially, from 2017 to 2019, there are sporadic periods of high coherency at shorter frequencies, indicating brief but strong interactions likely driven by market speculation and news events. From 2020 onwards, the coherency shows more variability with intermittent high coherency areas, particularly noticeable during market disruptions. Notably, in 2021 and 2022, there are several periods of increased coherency at both short and longer frequencies, suggesting that during these times, BTC and XRP prices moved more closely together, likely in response to significant market events or regulatory news. By 2023, there is a mix of high and low coherency patches, reflecting fluctuating interactions as market conditions and investor behaviors evolve. Overall, the graph highlights how BTC and XRP exhibit periods of strong co-movement, particularly during times of market stress, while also having phases of independent movement.

Similarly, the wavelet coherency between Bitcoin and Litecoin shows strong and evolving interactions across different time frames. From 2017 to 2019, there are extensive areas of high coherency at shorter frequencies, indicating that BTC and LTC had strong short-term price movements in sync during this period, likely driven by market speculation and similar investor sentiment. The period from 2020 onwards demonstrates sustained high coherency across both short and long frequencies, with significant red areas, especially noticeable during major market events such as the COVID-19 pandemic. This suggests that during these turbulent times, BTC and LTC moved closely together, reflecting their similar reactions to broader market dynamics. The coherency remains relatively high through 2021 and 2022, indicating a continued strong relationship between the two cryptocurrencies, although some fluctuations are observed. By 2023, the graph shows patches of high coherency, particularly at longer frequencies, highlighting a persistent long-term relationship. Overall, the graph illustrates that BTC and LTC have maintained a somewhat consistent co-movement over time until recent times. However, the most recent bull-run did not include LTC, which implies that there are factors beyond cryptocurrency platforms such as Bitcoin ETFs leaving out LTC out of the equation.

The relationship between Bitcoin and Tether is quite different as it reveals generally low coherency across most time frames, as indicated by the predominantly blue areas. This pattern reflects the stable nature of USDT as a stablecoin, which is designed to maintain a constant value, resulting in low co-movement with BTC, a highly volatile asset. However, there are sporadic instances of higher coherency, particularly at shorter frequencies and during specific periods such as late 2017 and early 2021, indicating brief episodes of stronger interaction likely due to market stress or significant trading activity involving both assets. These red and yellow patches suggest that during these times, movements in BTC were more synchronized with fluctuations in USDT, possibly due to investors converting between BTC and USDT in response to market volatility. Overall, the graph highlights that while BTC and USDT generally exhibit low coherency, their relationship can temporarily intensify during periods of market turbulence or significant trading volume.

In summary, wavelet analysis reveal that Bitcoin (BTC) has strong and dynamic relationships with Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and Litecoin (LTC), particularly during periods of market stress and significant events. These relationships are characterized by high coherency at various frequencies, indicating synchronized price movements driven by similar market dynamics. Since 2021, the coherency between BTC and ETH has notably increased, reflecting their dominant roles in the market. BTC and BNB show sustained high coherency post-2020, highlighting their strong long-term interaction which gets even stronger. There is somewhat fluctuating coherency between BTC and XRP as well as BTC and LTC with notable synchronization during major events. However, this relationship seems to be fading over time. In contrast, BTC and USDT generally display low coherency due to USDT's stablecoin nature, with occasional spikes during periods of high market activity or volatility.

Next, as an alternative to coherency analysis, we also performed a linear regression model examines the relationship between Bitcoin (BTC) and five other cryptocurrencies: pairwise where results are reported in Table 3. The residuals indicate a good fit overall, with most residuals close to zero, suggesting that the model's predictions are generally accurate. The coefficients for ETH (0.3696), USDT (0.2269), BNB (0.1095), and LTC (0.1885) are all positive and statistically significant, indicating that increases in these cryptocurrencies are associated with increases in BTC. Specifically, ETH shows the strongest positive relationship with BTC, where a 1% increase in ETH is associated with approximately a 0.37% increase in BTC. Conversely, XRP's coefficient (0.0071) is not statistically significant, implying no strong predictive relationship with BTC.

Overall, the model is highly significant, with an F-statistic of 992.2 and a p-value less than 0.001, indicating that the included variables collectively explain a significant portion of BTC's variability. The multiple R-squared value of 0.6668 suggests that about 66.68% of the variance in BTC's price can be explained by the model, while the adjusted R-squared value of 0.6661 accounts for the number of predictors, affirming the model's robustness. The intercept is not statistically significant, meaning the mean BTC value, when all predictors are zero, does not differ significantly from zero. This analysis underscores the strong interconnectedness between BTC and other major cryptocurrencies like ETH, USDT, BNB, and LTC, while XRP does not exhibit a significant relationship.

As OLS regression estimates the coefficient values around the mean of the dependent variable distribution, it may not effectively capture relationships in the tails of the distribution, especially in the presence of skewness or outliers, as indicated by measures like skewness and kurtosis. Also, the variables used in the OLS regression are highly correlated to the point where multicollinearity is a serious issue. In this context, OLS might fail to reveal important connections in the extremes of the data where such relationships could differ significantly from those around the mean. This limitation is particularly relevant when dealing with financial data, which often exhibits such characteristics.

Table 3. OLS estimate of BTC against ETH, USDT, BNB, XRP and LTC

Coefficients:	Estimate	se	t-value	p-value
Intercept	0.0005	0.0004	1.0810	0.28
ETH	0.3696	0.0169	21.9040	<2e-16***
USDT	0.2269	0.1064	2.1340	0.033*
BNB	0.1095	0.0092	11.8410	<2e-16***
XRP	0.0071	0.0099	0.7110	0.477
LTC	0.1885	0.0146	12.9490	<2e-16***

To overcome these issues, the method that we propose is pairwise quantile regression, which provides a more comprehensive analysis by estimating the relationships at different points (quantiles) of the dependent variable distribution. Specifically, it examines the relationship between each independent variable at the lowest 25% (lower quantile), the median (50% quantile), and the uppermost 25% (upper quantile) values of the dependent variable. This approach allows for a nuanced understanding of how the relationships may vary across different parts of the distribution, capturing the dynamics that OLS might miss, especially in the tails. Therefore, pairwise quantile regression is particularly useful for analyzing data with significant skewness or kurtosis, as it can uncover varying impacts of the independent variables across the entire distribution of the dependent variable.

Table 4 presents the results of Quantile-Quantile (Q-Q) regressions for Bitcoin against Ethereum, Tether, Binance Coin, Ripple, and Litecoin. The regressions are performed at three different quantiles: the 25th percentile (lower quantile), the median (50th percentile), and the 75th percentile (upper quantile) of the BTC distribution. This approach provides insights into how the relationships between BTC and the other cryptocurrencies vary across different parts of the BTC return distribution.

The intercept values vary across the different quantiles, indicating the baseline value of BTC when the independent variables (cryptocurrencies) are zero. For the 25th percentile, the intercepts are negative, suggesting lower baseline BTC values in this quantile. At the median and 75th percentile, intercept values are closer to zero or positive, indicating higher baseline

Table 4. Pairwise Quantile-quantile regression of Bitcoin against others

	X25coef	t25	X50coef	t50	X75coef	t75
intercept	–0.0091	–17.8012	0.0002	0.8664	0.0097	18.3434
ETH	0.6072	66.4932	0.6307	134.7885	0.6773	142.2536
intercept	–0.0141	–15.4591	0.0011	2.2158	0.0175	21.2409
USDT	0.5295	2.6504	0.3147	2.8866	0.4870	2.4915
intercept	–0.0130	–20.7752	–0.0008	–1.8884	0.0126	17.5592
BNB	0.4124	167.1867	0.4398	69.4700	0.4804	70.9692
intercept	–0.0116	–17.8002	0.0013	3.2140	0.0130	20.4172
XRP	0.3947	128.0810	0.4586	80.3034	0.4903	51.8116
intercept	–0.0096	–19.3026	0.0009	2.4403	0.0124	20.5821
LTC	0.5255	74.2007	0.5526	118.3809	0.6053	64.7856

BTC values. However, it is worth to note that the t-values for intercept terms are mostly insignificant.

The slope coefficients are all positive with a variation in power. The coefficients for ETH across all quantiles are significant and increase slightly from the 25th percentile (0.6072) to the 75th percentile (0.6773). This indicates a strong and consistent positive relationship with BTC across all quantiles, with a slightly stronger effect in the upper quantile. The coefficients for BNB are significant and increase from the 25th percentile (0.4124) to the 75th percentile (0.4804). This indicates that BNB has a strong positive relationship with BTC, with its influence growing in the upper quantiles. The coefficients for XRP are significant and also increase from the 25th percentile (0.3947) to the 75th percentile (0.4903). This pattern shows a consistent and increasing positive relationship with BTC across all quantiles. The coefficients for LTC are significant and increase from the 25th percentile (0.5255) to the 75th percentile (0.6053). This suggests that LTC has a strong positive relationship with BTC, which becomes more pronounced in the upper quantile. The coefficients for USDT show significant positive relationships across all quantiles, with the strongest effect at the 25th percentile (0.5295), which suggests that USDT has a more pronounced impact on BTC in the lower quantile, which may be associated with periods of market stress where stablecoins like USDT are heavily utilized in buying and selling other cryptoassets.

The ANOVA tests provide statistical validation for the variations in the quantile-quantile relationships between BTC and the other cryptocurrencies. The results indicate that while the relationship is homogeneous between the lower quantile and the median, it becomes heterogeneous when comparing the lower quantile to the upper quantile and the median to the upper quantile. This suggests that the co-movement between BTC and the other cryptocurrencies is more consistent in the middle of the distribution but varies significantly in the extremes, particularly during high return periods. This heterogeneous behavior at the extremes highlights the importance of considering different market conditions when analyzing the interconnectedness of cryptocurrencies. The results are visualized in Figure 5.

As shown in Figure 5, the ETH coefficient increases from approximately 0.60 at the lower quantiles (0.1) to around 0.70 at the higher quantiles (0.8 and above). The increasing trend in the ETH coefficient across quantiles indicates that the positive relationship between ETH and BTC strengthens as we move from lower to higher quantiles. This suggests that during higher return periods for BTC (upper quantiles), ETH has a stronger impact on BTC returns compared to lower return periods (lower quantiles). The widening confidence intervals at higher quantiles suggest increased variability and less precision in the coefficient estimates at these levels, potentially due to higher volatility in BTC returns during these periods. We observe the same type of relationship between BTC and LTC where the relationship between them is more emphasized during positive periods.

Similarly, the BNB and XRP coefficients also increase across the quantiles, indicating progressively stronger positive relationships with BTC as BTC returns move from lower to higher quantiles. This suggests that BNB and XRP's influence on BTC returns is more pronounced during periods of higher BTC returns, highlighting the importance of considering different quantiles to understand the full range of their relationship. The slight dip in the coefficient at the very upper quantile also points to potential complexities in their interaction during extreme market conditions.

The only exception is USDT vs BTC where the USDT coefficient shows significant variability across different quantiles of the BTC return distribution, indicating a complex and non-linear relationship. During periods of low and high BTC returns, USDT's impact on BTC is moderate but uncertain, as reflected by the wide confidence intervals. In the median range, USDT's impact is more stable and consistent. This suggests that USDT's relationship with BTC varies significantly across different market conditions, emphasizing the need to consider different quantiles to fully understand their interaction. The wide confidence intervals at the extremes highlight the increased uncertainty and variability in the relationship during these periods.

Results highlight that interactions among cryptocurrencies cannot be solely characterized by global correlations, as the decomposed correlation structure reveals varying association levels across different time frames. This variation provides better opportunities for diversification when considering timing effects. Notably, USDT may exhibit a negative relationship with other cryptocurrencies in the short term, but this can reverse to a positive relationship in the medium term, indicating the need for careful consideration of time horizons. Different pairs of cryptocurrencies, such as BTC-ETH and BTC-BNB, show fundamental linkages and contagion effects that intensify during turbulent periods, while BTC-USDT interactions are characterized by transient 'fast and furious' correlations that dissipate quickly. The Q-Q regressions reveal heterogeneous interconnections in the extremes, indicating that Bitcoin's responses to alternative cryptocurrencies differ during market crashes and booms.

Overall, our study concludes that the co-movement among major cryptocurrencies can increase significantly during crises, reflecting stronger fundamental linkages and greater connectedness with the broader economy. However, Tether stands out as an exception to this trend. These findings have important implications for managing expected losses in investment portfolios that include cryptocurrencies or ETFs based on these assets.

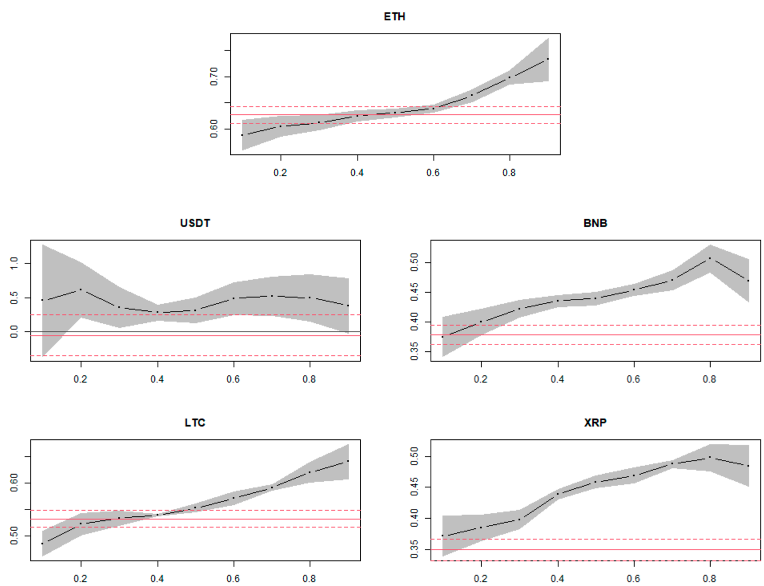

Figure 5. Slope coefficient values at different quantiles for each pair against BTC

6. Conclusions

In this study, we used a hybrid approach to examine the dynamics of major cryptocurrencies through wavelet coherence and quantile-quantile regressions. The analysis spanned from the cryptocurrency boom in 2017, through crises like the COVID-19 pandemic, the Russian-Ukrainian war, and the Silicon Valley Bank financial distress, to the post-ETF approval cryptoboom. Wavelet analysis decomposed cryptocurrency log-returns into different scales, highlighting correlations across various time frames. We found that long-run relationships were more prominent than medium-run ones, with interconnection levels fluctuating over time. Specifically, the wavelet coherency analysis showed BTC's significant relationships with ETH, BNB, XRP, and LTC, with high coherency during market turbulence, indicating both fundamental linkages and contagion effects. BTC-BNB coherency increased from 2020, reflecting stronger connections due to BNB's role in the Binance ecosystem. BTC-XRP displayed strong coherency during market disruptions, suggesting fundamental linkages and intermittent contagion effects. In contrast, BTC and USDT generally showed low coherency, with spikes during high trading volumes or market stress. Pairwise quantile-quantile regressions revealed that ETH, BNB, XRP, and LTC had positive relationships with BTC, especially during higher BTC returns, indicating their role in driving BTC's performance during bullish markets. USDT had a stabilizing influence on BTC during extreme conditions, aligning with its role as a stablecoin. These findings highlight the diverse nature of BTC's interactions with different cryptocurrencies, emphasizing the need to consider varying market conditions and the specific roles of each cryptocurrency.

We adressed the key questions about the cryptocurrency market by highlighting several crucial points. First, global correlations primarily reflect long-term associations among cryptocurrencies, with Bitcoin showing synchronization with other major cryptocurrencies, except for Tether. Crises do not always disrupt recovery and growth phases, but they can significantly deepen recessions during downward trends. Fundamental linkages drive the co-movement among major cryptocurrencies, amplifying short-term excess co-movement, with Tether being an exception. The study also reveals that the nexus among cryptocurrencies is heterogeneous, with Bitcoin being more sensitive to positive extremes than to negative ones. These findings underscore the importance of considering different time frames and external economic events when analyzing cryptocurrency markets. Using wavelet coherence and quantile-quantile regressions, the research uncovers both long-term fundamental connections and short-term contagion effects, providing valuable insights for investment portfolio management.

The study also suggests that dynamic diversification, by incorporating the term structure of correlation, can optimize returns and manage risks effectively, especially during periods of market volatility. Investors should adjust their strategies according to the current market cycle, recognizing that economic crises can disrupt upward trends or deepen downturns. Insights into the types of linkages driving cryptocurrency co-movement can guide decisions on whether to adopt active, passive, or hybrid management strategies. Policymakers face a dual challenge: cushioning the effects of potential market disruptions caused by cryptocurrencies while fostering innovation and investment. Implementing regulatory frameworks to monitor the impact of cryptocurrencies on financial markets and enhancing risk management practices are crucial. Balancing investor protection with supporting financial stability will harness the benefits of cryptocurrencies while safeguarding the broader economy.

As a limitation, we selected cryptocurrencies based on market capitalization without limiting them by category, relying heavily on historical data, which might have skewed our results. We also did not differentiate between types of cryptocurrencies, such as payment coins, stablecoins, and utility tokens, potentially missing important market details. This lack of differentiation could mean our results do not fully capture the nuances within the cryptocurrency market. Incorporating more cryptocurrencies could reduce the number of observations and affect findings, suggesting the need for a broader dataset. Future research should consider analyzing cryptocurrencies within the same category or expanding the range of variables to gain a more detailed understanding, especially during periods of market volatility. Additionally, investigating cryptocurrency behavior during extreme market periods could provide valuable insights into their resilience and vulnerabilities, offering practical implications for risk management and policy-making.

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Author contributions

BYA conceived the research idea and conducted data collection. OG performed initial wavelet analysis and finalized the draft. JCTG conducted detailed data analysis and quantile regressions. All authors contributed to the final draft.

Disclosure statement

Authors may have invested in cryptocurrencies mentioned in this article.

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