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Frequency-Dependent Return Connectedness among Major Cryptocurrencies: Evidence from the Indian Cryptocurrency Market

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ABSTRACT

Understanding return transmission across cryptocurrency markets is important for portfolio diversification and risk management. This study examines frequency-specific connectedness among Bitcoin, Ethereum, Cardano, Stellar, and Ripple in the Indian cryptocurrency market using daily INR-denominated prices from March 2018 to December 2025. The Baruník and Křehlík (2018) framework decomposes return spillovers across short-, medium-, and long-term horizons. The findings reveal moderate overall connectedness (TCI = 51.50%), with spillovers concentrated in the short term and weakening considerably over longer horizons. Cardano is the dominant transmitter, while Ethereum also transmits shocks. Ripple is the principal receiver, whereas Bitcoin becomes a transmitter over longer horizons, with implications for diversification, risk management, and regulatory policy.

Keywords: Cryptocurrency, Return Connectedness, Frequency Connectedness, Indian Cryptocurrency Market, Portfolio Diversification.

JEL Classification: C32, C58, G11, G15, G17

INTRODUCTION

The rapid evolution of financial technology has transformed the global financial system, with cryptocurrencies emerging as a major class of digital assets. Since the introduction of Bitcoin, the cryptocurrency market has expanded through assets such as Ethereum, Cardano, Stellar, and Ripple, attracting increasing participation from retail and institutional investors. Their growing adoption for investment, payment systems, and decentralised finance has strengthened their integration with financial markets. However, cryptocurrencies remain highly volatile and subject to rapid information transmission, making the analysis of market connectedness important for portfolio management, risk assessment, and financial stability.

Financial connectedness examines how shocks originating in one asset are transmitted to others and provides important insights into market integration, systemic risk, contagion, and diversification opportunities. While conventional connectedness measures capture aggregate spillover effects, they do not distinguish between temporary and persistent shocks. Because investors operate across different investment horizons, the magnitude and direction of spillovers may vary across short-, medium-, and long-term periods. Consequently, frequency-domain analysis provides a more comprehensive understanding of return transmission across different investment horizons.

The frequency connectedness framework proposed by Baruník and Křehlík (2018) represents an important methodological advancement by decomposing connectedness across different investment horizons. The framework distinguishes transitory spillovers from more persistent interdependencies and has been widely applied across financial and cryptocurrency markets. Previous studies indicate that cryptocurrency connectedness is dynamic and influenced by market uncertainty, investor sentiment, financial crises, and macroeconomic conditions, with stronger spillovers generally observed over shorter investment horizons (Mensi et al., 2021; Polat & Kabakçı Günay, 2021; Fousekis & Tzaferi, 2021; Mo et al., 2022; Hanif et al., 2023; Long et al., 2024).

Despite the growing literature, important research gaps remain. Most studies focus on global cryptocurrency markets or USD-denominated assets, with comparatively limited evidence from country-specific markets, particularly emerging economies. The Indian cryptocurrency market provides an important setting for examining these dynamics because of its evolving digital asset ecosystem and increasing market participation. Nevertheless, empirical evidence on horizon-specific connectedness among major cryptocurrencies in the Indian market remains limited. Moreover, relatively few studies simultaneously examine Bitcoin (BTC_INR), Ethereum (ETH_INR), Cardano (ADA_INR), Stellar (XLM_INR), and Ripple (XRP_INR) across multiple investment horizons using INR-denominated prices.

Accordingly, this study employs the frequency connectedness framework developed by Baruník and Křehlík (2018) to investigate horizon-specific return spillovers among Bitcoin (BTC_INR), Ethereum (ETH_INR), Cardano (ADA_INR), Stellar (XLM_INR), and Ripple (XRP_INR) in the Indian cryptocurrency market. Unlike many existing studies that focus primarily on global cryptocurrency markets or USD-denominated assets, this study provides frequency-domain evidence from an emerging economy using INR-denominated cryptocurrency prices. By identifying the dominant transmitters and receivers of return spillovers across short-, medium-, and long-term investment horizons, the study contributes to the frequency connectedness literature and offers practical implications for portfolio diversification, risk management, and regulatory decision-making in the Indian cryptocurrency market.

REVIEW OF LITERATURE

The concept of financial connectedness has evolved considerably over the past decade, providing increasingly sophisticated frameworks for understanding shock transmission across financial markets. Diebold and Yilmaz (2012) introduced a generalized vector autoregressive (VAR) framework to quantify total and directional spillovers using forecast error variance decompositions, which was subsequently extended through network topology to capture systemic interconnectedness more effectively (Diebold & Yilmaz, 2014). Recognising that financial markets behave differently across investment horizons, Baruník and Křehlík (2018) proposed the frequency connectedness framework, which decomposes connectedness into short-, medium-, and long-term components. This methodological advancement enables researchers to distinguish temporary market disturbances from persistent structural spillovers and has become one of the most widely adopted approaches in connectedness research.

Building upon these methodological developments, numerous studies have applied the frequency-domain framework to conventional financial markets. Existing evidence consistently demonstrates that spillover intensity varies across investment horizons rather than remaining constant over time. Short-term connectedness generally dominates long-term spillovers, while financial crises amplify volatility transmission and reduce diversification opportunities (Naeem et al., 2020; Li et al., 2021; Shah et al., 2021; Bagheri et al., 2022; Umar et al., 2022). Collectively, these studies establish that investment horizon is a critical determinant of market interconnectedness, portfolio diversification, and systemic risk.

The application of frequency connectedness has expanded rapidly within cryptocurrency markets because of their high volatility, speculative nature, and growing integration with the global financial system. Existing studies consistently report that cryptocurrency connectedness is dynamic, frequency dependent, and influenced by market uncertainty. Bitcoin and Ethereum frequently emerge as dominant transmitters of volatility spillovers, while spillover intensity is generally stronger over short investment horizons than over medium- and long-term horizons (Mensi et al., 2021; Polat & Kabakçı Günay, 2021; Fousekis & Tzaferi, 2021; Cui & Maghyereh, 2022; Katsiampa et al., 2022; Nyakurukwa & Seetharam, 2023; Hanif et al., 2023; Long et al., 2024; Ghazani et al., 2024; Esparcia et al., 2024; Assaf et al., 2024). Furthermore, higher-order moments, trading activity, investor sentiment, and jump risks have been identified as important determinants of connectedness, suggesting that spillovers extend beyond conventional return and volatility dynamics (Fousekis & Tzaferi, 2021; Cui & Maghyereh, 2022; Hanif et al., 2023; Long et al., 2024).

A growing body of evidence also highlights the sensitivity of cryptocurrency connectedness to periods of economic and financial stress. Market disruptions, including the COVID-19 pandemic and the collapse of FTX, significantly intensified volatility transmission, strengthened market interconnectedness, and reduced diversification opportunities (Polat & Kabakçı Günay, 2021; Katsiampa et al., 2022; Ghazani et al., 2024; Esparcia et al., 2024). These findings indicate that spillover structures evolve over time and are strongly influenced by changing market conditions and investor behaviour.

Recent studies have broadened the scope of connectedness analysis by examining the interactions between cryptocurrencies and other financial markets. Evidence suggests that cryptocurrencies exhibit dynamic spillovers with commodity, energy, Islamic equity, FinTech, environmental, and sustainable finance markets, although the magnitude and direction of transmission vary across asset classes and investment horizons (Mo et al., 2022; Prasad Yadav et al., 2022; Marco et al., 2023; Mezghani et al., 2024; Rao et al., 2024; Assaf et al., 2024). Similarly, increasing attention has been devoted to understanding the relationship between cryptocurrencies and green finance. Studies involving green bonds, renewable energy, electricity markets, carbon markets, DeFi, and environmentally related financial assets consistently demonstrate that connectedness is frequency dependent and becomes stronger during periods of heightened uncertainty (Zeng et al., 2025; Niu & Liu, 2025; Gök, 2025; Jeribi & Béjaoui, 2025; Ameur et al., 2025; Shao, 2025).

Recent literature further confirms that cryptocurrency connectedness has become increasingly complex owing to technological innovation, regulatory developments, geopolitical uncertainty, and evolving market structures. Systematic reviews and empirical studies conclude that advanced frequency-domain methodologies provide deeper insights into the dynamic nature of volatility spillovers and systemic risk than conventional time-domain approaches (Adelopo & Luo, 2025; Nițoi et al., 2025; Haq et al., 2025; Gunay et al., 2025; Woode et al., 2025; Khattobov et al., 2025). Overall, the literature demonstrates a clear transition from measuring static spillovers toward understanding the frequency-dependent and multidimensional behaviour of interconnected cryptocurrency markets.

Research gap

Despite the growing literature on cryptocurrency connectedness, important research gaps remain. Most existing studies focus on global cryptocurrency markets, cross-asset spillovers, or USD-denominated cryptocurrencies, with comparatively limited evidence from country-specific markets, particularly emerging economies. Moreover, although the frequency connectedness framework of Baruník and Křehlík (2018) has been widely applied, horizon-specific return spillover dynamics among major cryptocurrencies in the Indian market remain largely unexplored. Given the evolving Indian cryptocurrency market and its increasing integration with global digital asset markets, examining frequency-specific connectedness is particularly relevant. This study addresses these gaps by applying the Baruník and Křehlík (2018) framework to examine frequency-specific connectedness among Bitcoin (BTC_INR), Ethereum (ETH_INR), Cardano (ADA_INR), Stellar (XLM_INR), and Ripple (XRP_INR) using INR-denominated prices. The study contributes to the literature by providing evidence from an emerging economy and offering practical implications for portfolio diversification, risk management, and regulatory decision-making.

Research Objectives

1. To examine the return characteristics and correlation structure among Bitcoin (BTC_INR), Ethereum (ETH_INR), Cardano (ADA_INR), Stellar (XLM_INR), and Ripple (XRP_INR) in the Indian cryptocurrency market.

2. To estimate the overall connectedness among the selected cryptocurrencies using the Baruník and Křehlík (2018) frequency connectedness framework.

3. To analyse frequency-specific return spillovers among the selected cryptocurrencies across short-, medium-, and long-term investment horizons.

4. To identify the directional transmission of return spillovers by determining the net transmitters and net receivers of shocks using TO, FROM, NET, pairwise connectedness, and Influence Index measures.

5. To assess the implications of frequency-specific connectedness for portfolio diversification, risk management, and investment decision-making in the Indian cryptocurrency market.

METHODOLOGY

This study examines frequency-specific connectedness among five major cryptocurrencies in the Indian market, namely Bitcoin (BTC_INR), Ethereum (ETH_INR), Cardano (ADA_INR), Stellar (XLM_INR), and Ripple (XRP_INR). The five cryptocurrencies were selected based on their market relevance, established presence in the cryptocurrency ecosystem, and representation among major digital assets, providing a diverse set of widely recognized cryptocurrencies for analysing return spillovers and market interconnectedness. The analysis uses daily closing prices denominated in Indian Rupees (INR), obtained from Investing.com, covering the period from March 2018 to December 2025.

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

where $R_{i,t}$ denotes the logarithmic return of cryptocurrency i at time t, $P_{i,t}$ represents its closing price at time t, and $P_{i,t-1}$ denotes the closing price on the preceding day. Logarithmic returns transform price levels into continuously compounded returns and facilitate the statistical modelling of financial time series. Descriptive statistics and Pearson correlation analysis are conducted as preliminary analyses to examine the distributional characteristics and linear interrelationships among the selected cryptocurrency returns.

To examine the stationarity of the return series, the Augmented Dickey-Fuller (ADF) test was applied to each cryptocurrency return series. The null hypothesis of the ADF test is that the series contains a unit root, while the alternative hypothesis indicates stationarity. The results reject the null hypothesis of a unit root for all five cryptocurrency return series at the 1% significance level. The ADF statistics are −12.876 for BTC_INR, −12.742 for ETH_INR, −12.637 for ADA_INR, −13.687 for XLM_INR, and −13.414 for XRP_INR, with p-values below 0.01. These results confirm that all return series are stationary and therefore suitable for subsequent VAR estimation and frequency connectedness analysis.

The empirical analysis begins with the estimation of a Vector Autoregressive (VAR) model using the daily logarithmic return series. The optimal lag length was selected using the Akaike Information Criterion (AIC), which indicated three lags; accordingly, a VAR(3) specification was employed to capture the dynamic interdependencies among the five cryptocurrencies. The estimated VAR provides the coefficient and residual covariance matrices required for the generalized forecast error variance decomposition (GFEVD). The generalized forecast error variance decomposition is invariant to the ordering of variables and therefore avoids the ordering dependence associated with orthogonalized decompositions. The VAR estimation uses 2,859 observations after accounting for the lag structure.

Following Baruník and Křehlík (2018), the GFEVD is estimated over a 100-period forecast horizon and transformed into the frequency domain. The frequency decomposition is specified using three bands: 1–5 days, 5–20 days, and 20–∞ days, representing short-, medium-, and long-term investment horizons, respectively. This decomposition enables the identification of the extent to which return spillovers are concentrated in shorter horizons or persist over longer periods.

Based on the frequency-specific GFEVD, the Total Connectedness Index (TCI), directional connectedness TO and FROM, Net Directional Connectedness (NET), Net Pairwise Connectedness (NPC), and Influence Index are estimated. These measures capture the overall degree of connectedness, the direction and magnitude of return spillovers transmitted and received by each cryptocurrency, and the relative roles of individual cryptocurrencies as net transmitters or receivers of shocks. The frequency-specific connectedness measures are subsequently presented through spillover network graphs to illustrate the direction and relative intensity of return transmission among Bitcoin, Ethereum, Cardano, Stellar, and Ripple.

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RESULTS

ADF Unit Root Test Results

Table 1. Augmented Dickey-Fuller Unit Root Test Results

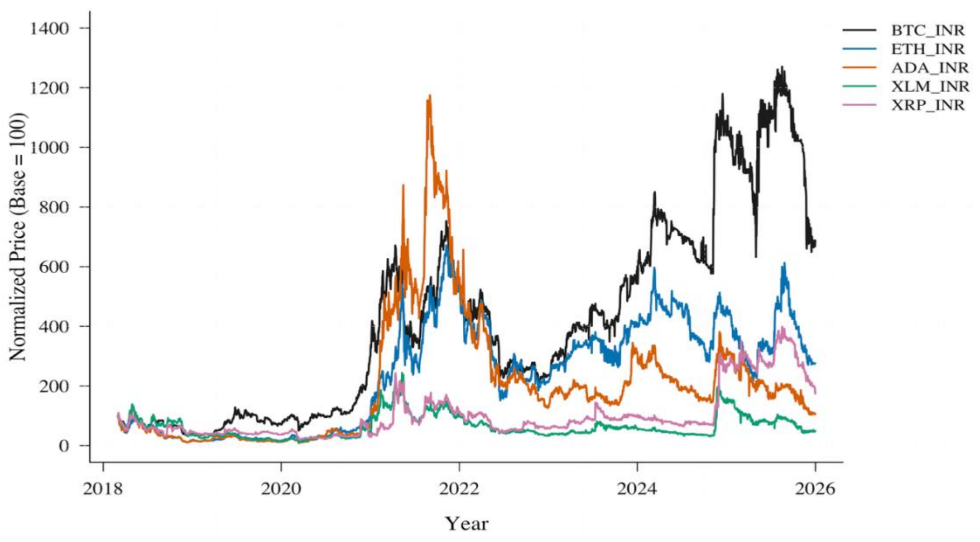
Cryptocurrency	ADF Statistic	p-value
BTC_INR	−12.876	< 0.01
ETH_INR	−12.742	< 0.01
ADA_INR	−12.637	< 0.01
XLM_INR	−13.687	< 0.01
XRP_INR	−13.414	< 0.01

Note: The ADF test is applied to daily logarithmic return series. The null hypothesis is that the series contains a unit root. All reported p-values are below 0.01.

Table 1 presents the results of the Augmented Dickey-Fuller (ADF) unit root test applied to the daily logarithmic return series of the five selected cryptocurrencies. The ADF statistics are statistically significant at the 1% level for all series, leading to rejection of the null hypothesis of a unit root. The results confirm that all return series are stationary and suitable for the subsequent VAR and frequency connectedness analysis.

Preliminary Analysis of Cryptocurrency Prices and Returns

Figure 1. Normalized Daily Price Series of Selected Cryptocurrencies



Source: Authors' computations based on daily INR-denominated cryptocurrency data.

Figure 1 presents the normalized daily price series (Base = 100) of Bitcoin (BTC_INR), Ethereum (ETH_INR), Cardano (ADA_INR), Stellar (XLM_INR), and Ripple (XRP_INR) in the Indian cryptocurrency market from March 2018 to December 2025. Normalization facilitates comparison of the relative price movements of the selected cryptocurrencies by removing differences in their initial price levels. The figure shows substantial fluctuations, with a pronounced market expansion during 2020–2021, followed by a sharp correction in 2022 and heterogeneous recovery patterns during 2023–2025. Bitcoin records the strongest long-term price appreciation, while Cardano exhibits the most pronounced short-term surge during the 2021 cryptocurrency

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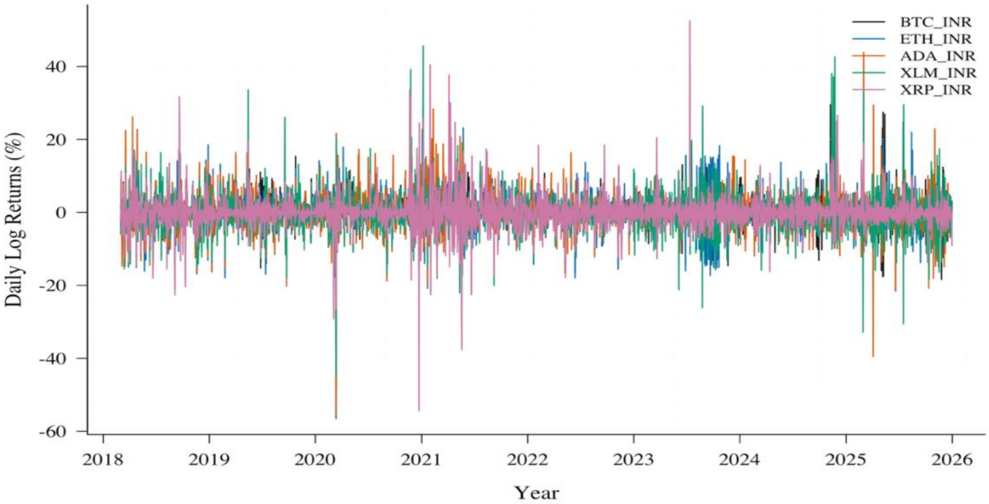
boom. Ethereum also shows substantial growth, whereas Ripple and Stellar display comparatively moderate price movements. The heterogeneous price trajectories indicate differences in asset-specific market behaviour and provide preliminary evidence of varying return dynamics across cryptocurrencies. These patterns provide descriptive motivation for the subsequent frequency-specific connectedness analysis based on the Baruník and Křehlík (2018) framework.

Figure 2. Daily Log Return Series of Selected Cryptocurrencies



Source: Authors' computations based on daily INR-denominated cryptocurrency data.

Figure 2 presents the daily logarithmic return series of Bitcoin (BTC_INR), Ethereum (ETH_INR), Cardano (ADA_INR), Stellar (XLM_INR), and Ripple (XRP_INR) in the Indian cryptocurrency market from March 2018 to December 2025. The returns fluctuate around a mean close to zero and exhibit clear volatility clustering, characterised by alternating periods of relatively low and high return variability. Several episodes of extreme positive and negative returns are observed, particularly during 2020–2021 and 2024–2025, indicating periods of heightened return variability and rapid price adjustments. Cardano, Stellar, and Ripple display relatively larger return fluctuations than Bitcoin and Ethereum, suggesting greater short-term return variability. Overall, the series exhibit characteristic features of cryptocurrency returns, including volatility clustering and extreme observations. These patterns provide preliminary motivation for applying the Baruník and Křehlík (2018) frequency connectedness framework to examine horizon-specific return spillovers among the selected cryptocurrencies.

Correlation Analysis

Table 2. Correlation Matrix of Selected Cryptocurrencies

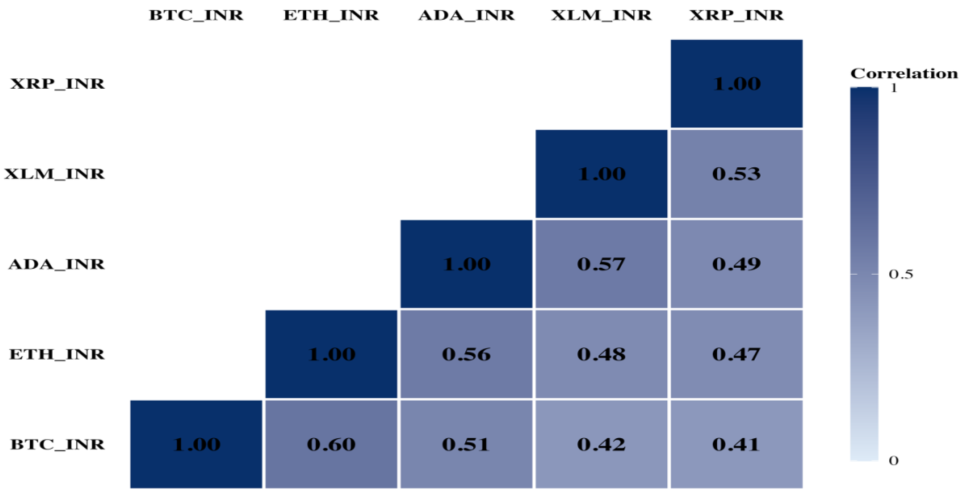
Cryptocurrency	BTC_INR	ETH_INR	ADA_INR	XLM_INR	XRP_INR
BTC_INR	1.0000	0.5987	0.5071	0.4165	0.4088
ETH_INR	0.5987	1.0000	0.5643	0.4772	0.4710
ADA_INR	0.5071	0.5643	1.0000	0.5678	0.4874
XLM_INR	0.4165	0.4772	0.5678	1.0000	0.5285
XRP_INR	0.4088	0.4710	0.4874	0.5285	1.0000

Source: Authors' computations based on daily INR-denominated cryptocurrency data.

Note: Pearson correlation coefficients are computed using the daily log returns of the selected cryptocurrencies.

Table 2 presents the Pearson correlation coefficients among the daily returns of the selected cryptocurrencies. All pairwise correlations are positive, indicating that the cryptocurrencies generally move in the same direction, although the strength of co-movement varies. The strongest correlation is observed between BTC_INR and ETH_INR (0.5987), followed by ADA_INR with XLM_INR (0.5678) and ETH_INR (0.5643), indicating relatively stronger co-movement among these assets. In contrast, BTC_INR exhibits comparatively weaker correlations with XLM_INR (0.4165) and XRP_INR (0.4088), indicating lower synchronous return movements. As none of the correlation coefficients exceed 0.60, the results indicate moderate pairwise co-movement among the selected cryptocurrencies. Overall, the findings provide preliminary evidence of market interconnectedness while indicating that each cryptocurrency retains a degree of independent return behaviour. These results support the subsequent application of the Baruník and Křehlík (2018) frequency connectedness framework to examine return spillovers across different investment horizons.

Figure 3. Correlation Heatmap of Selected Cryptocurrencies.



Source: Authors' computations based on daily INR-denominated cryptocurrency data.

Figure 3 presents the heatmap of the Pearson correlation coefficients among the daily log returns of Bitcoin (BTC_INR), Ethereum (ETH_INR), Cardano (ADA_INR), Stellar (XLM_INR), and Ripple (XRP_INR). The heatmap visually complements the correlation matrix reported in Table 2, with darker shades indicating stronger positive correlations. All cryptocurrency pairs exhibit positive correlations, indicating that the selected assets generally move in the same direction under common market conditions. The strongest association is observed between Bitcoin and Ethereum (0.60), followed by Cardano and Stellar (0.57), while the weakest relationship is between Bitcoin and Ripple (0.41). Overall, the correlations remain within a moderate range (0.41–0.60), indicating that the cryptocurrencies exhibit common return movements while retaining asset-specific characteristics. These findings provide preliminary evidence of market interconnectedness and support the subsequent application of the Baruník and Křehlík (2018) frequency connectedness framework to examine return spillovers across different investment horizons.

Overall Frequency Connectedness Analysis

Table 3. Overall Frequency Connectedness Matrix

Cryptocurrency	**BTC**	**ETH**	**ADA**	**XLM**	**XRP**	**FROM**
BTC	**50.04**	19.27	13.16	8.99	8.55	**49.96**

ETH	17.74	**45.80**	15.26	10.85	10.34	**54.20**
ADA	12.47	15.28	**45.95**	15.36	10.94	**54.05**
XLM	8.96	11.72	16.30	**49.03**	13.98	**50.97**
XRP	9.00	11.80	12.64	14.89	**51.67**	**48.33**
TO	**48.17**	**58.07**	**57.37**	**50.09**	**43.81**	
Net	**−1.79**	**3.87**	**3.32**	**−0.88**	**−4.51**	

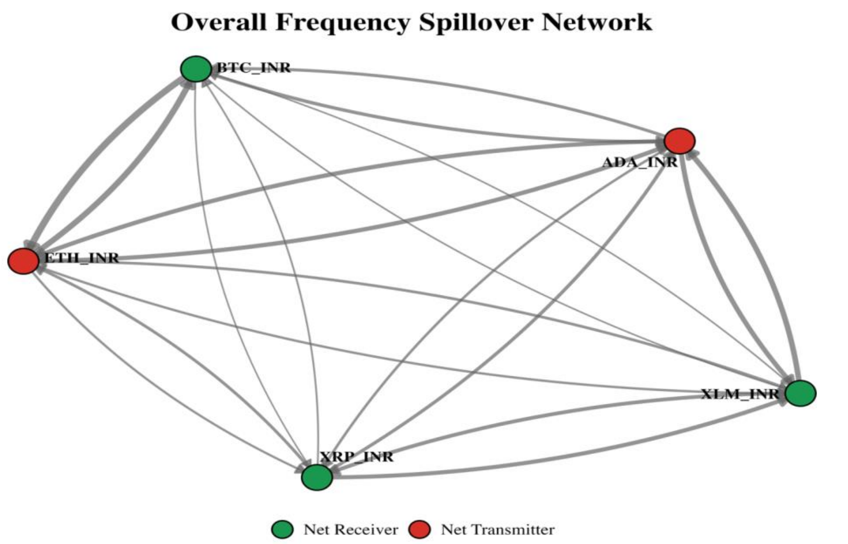
TCI = 51.50% **cTCI = 64.38%**

Source: Authors' computations based on daily INR-denominated cryptocurrency data.

Note: Diagonal elements represent own variance shares, while off-diagonal elements indicate directional spillovers based on the generalized forecast error variance decomposition. FROM and TO denote directional spillovers received and transmitted, respectively. Net = TO − FROM. TCI denotes the Total Connectedness Index, and cTCI denotes the corrected Total Connectedness Index.

Table 3 presents the overall connectedness matrix estimated using the Baruník and Křehlík (2018) frequency connectedness framework. The results indicate that own shocks explain 45.80% to 51.67% of the forecast error variance, while the remaining variation is attributable to cross-market spillovers, indicating a moderate degree of interconnectedness among the selected cryptocurrencies. Ethereum (TO = 58.07%) emerges as the strongest overall transmitter of return spillovers, followed by Cardano (TO = 57.37%), whereas Ripple (TO = 43.81%) contributes the least to overall spillover transmission. The net spillover measures identify Ethereum (NET = 3.87) and Cardano (NET = 3.32) as net transmitters, while Bitcoin (NET = −1.79), Stellar (NET = −0.88), and Ripple (NET = −4.51) function as net receivers. The TCI of 51.50% and cTCI of 64.38% indicate a moderate degree of overall connectedness, suggesting substantial cross-market return spillovers among the selected cryptocurrencies. These findings highlight the importance of accounting for connectedness in portfolio diversification and risk management and provide a basis for the subsequent frequency-specific analysis.

Figure 4. Overall Connectedness Network



Source: Authors' illustration based on the Baruník and Křehlík (2018) frequency connectedness framework.

Note: The network illustrates the overall spillover structure estimated using the Baruník and Křehlík (2018) frequency connectedness framework. Red nodes represent net transmitters, whereas green nodes represent net receivers. Directed edges indicate the direction of spillover transmission, and edge thickness is proportional to spillover intensity.

Figure 4 illustrates the overall spillover network among the selected cryptocurrencies estimated using the Baruník and Křehlík (2018) frequency connectedness framework. The network depicts the direction and relative magnitude of return spillovers, with red nodes representing net transmitters, green nodes representing net receivers, and edge thickness indicating spillover intensity. Consistent with Table 3, Ethereum (ETH) emerges as the strongest overall transmitter of return spillovers, followed by Cardano (ADA), while Bitcoin (BTC), Stellar (XLM), and Ripple (XRP) function as net receivers. The relatively thicker links associated with Ethereum and Cardano highlight their prominent roles in transmitting return spillovers across the market. Overall, the network reflects a moderate level of interconnectedness, consistent with the Total Connectedness Index (TCI) of 51.50%, indicating substantial cross-market return transmission. The figure complements the connectedness results by visually illustrating the overall pattern of return transmission before its decomposition into short-, medium-, and long-term investment horizons.

Frequency Connectedness Analysis

Short-Term Frequency Connectedness

Table 4. Short-Term Frequency Connectedness Matrix

Cryptocurrency	BTC_INR	ETH_INR	ADA_INR	XLM_INR	XRP_INR	FROM
BTC_INR	**42.75**	16.07	10.75	7.43	7.30	**41.55**
ETH_INR	14.10	**38.81**	12.54	8.95	8.64	**44.23**
ADA_INR	10.26	12.34	**38.92**	12.98	9.07	**44.66**
XLM_INR	7.28	9.30	12.85	**41.89**	11.35	**40.79**
XRP_INR	7.05	9.28	9.88	11.89	**41.82**	**38.10**
TO	**38.69**	**46.99**	**46.03**	**41.24**	**36.36**	
Net	**−2.85**	**2.76**	**1.38**	**0.45**	**−1.74**	
TCI (cTCI)						**41.86 (52.33)**

Source: Authors' computations using the Baruník and Křehlík (2018) frequency connectedness framework.

Note: Diagonal elements represent own variance shares, while off-diagonal elements indicate directional spillovers based on the generalized forecast error variance decomposition. FROM and TO denote directional spillovers received and transmitted, respectively. Net = TO − FROM. TCI denotes the Total Connectedness Index, and cTCI denotes the corrected Total Connectedness Index.

Table 4 reports the short-term frequency connectedness among the selected cryptocurrencies. The results indicate a moderate level of short-term interconnectedness, with a Total Connectedness Index (TCI) of 41.86% and a corrected Total Connectedness Index (cTCI) of 52.33%, indicating that approximately 42% of the forecast error variance is explained by cross-market spillovers. Own shocks account for 38.81% to 42.75% of the variance, with Bitcoin exhibiting the highest own variance share (42.75%), while Ethereum (38.81%) and Cardano (38.92%) exhibit relatively greater cross-market connectedness. Ethereum (TO = 46.99%) and Cardano (TO = 46.03%) emerge as the dominant transmitters of short-term shocks, whereas Ripple (TO = 36.36%)

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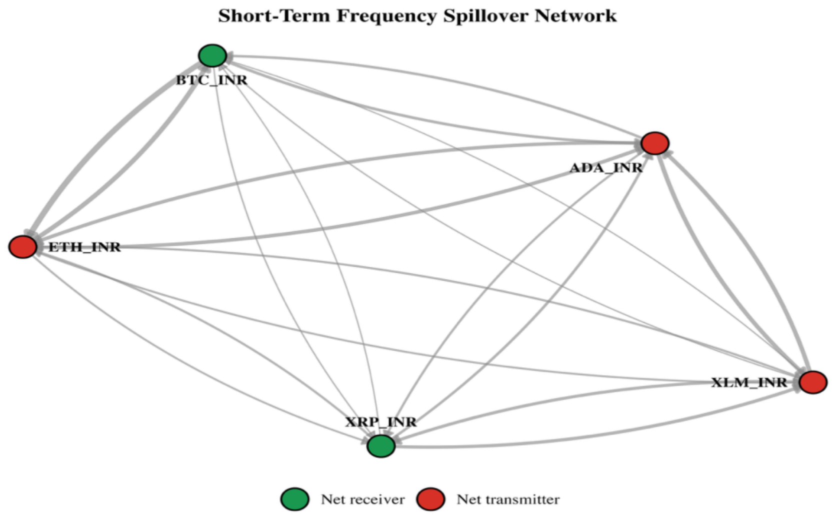
contributes the least. The net spillover measures identify Ethereum (NET = 2.76), Cardano (NET = 1.38), and Stellar (NET = 0.45) as net transmitters, while Bitcoin (NET = −2.85) and Ripple (NET = −1.74) function as net receivers. Compared with the overall connectedness reported in Table 3 (TCI = 51.50%), the short-term component represents the largest frequency-specific share of total connectedness, highlighting the importance of short-horizon return transmission in the cryptocurrency market. Nevertheless, the substantial short-term spillovers indicate that shocks can propagate across cryptocurrencies and have important implications for short-term portfolio diversification and risk management.

Figure 5. Short-Term Frequency Spillover Network



Source: Authors' illustration based on the Baruník and Křehlík (2018) frequency connectedness framework.

Note: The figure presents the short-term spillover network estimated using the Baruník and Křehlík (2018) frequency connectedness framework. Red nodes indicate net transmitters, while green nodes indicate net receivers. Directed edges represent the direction of spillover transmission, and edge widths are proportional to the magnitude of spillover effects.

Figure 5 illustrates the short-term spillover network among the selected cryptocurrencies estimated using the Baruník and Křehlík (2018) frequency connectedness framework. The network depicts the direction and relative intensity of short-term return spillovers, with red nodes representing net transmitters, green nodes representing net receivers, and edge thickness indicating spillover strength. Consistent with Table 4, Ethereum (ETH) and Cardano (ADA) emerge as the dominant transmitters of short-term shocks, while Stellar (XLM) acts as a relatively weaker net transmitter. In contrast, Bitcoin (BTC) and Ripple (XRP) function as net receivers, indicating greater susceptibility to shocks originating from other cryptocurrencies. The thicker links associated with Ethereum and Cardano highlight their prominent roles in short-term return transmission. Overall, the network reflects a moderate level of short-term interconnectedness, consistent with the Total Connectedness Index (TCI) of 41.86%, indicating that short-term spillovers are concentrated around a few influential cryptocurrencies while own-market effects remain important. These findings reinforce the prominent roles of Ethereum and Cardano in transmitting short-term return spillovers within the Indian cryptocurrency market.

Medium-Term Frequency Connectedness

Table 5. Medium-Term Frequency Connectedness Matrix

Cryptocurrency	BTC_INR	ETH_INR	ADA_INR	XLM_INR	XRP_INR	FROM
BTC_INR	**5.35**	2.36	1.77	1.14	0.93	**6.19**

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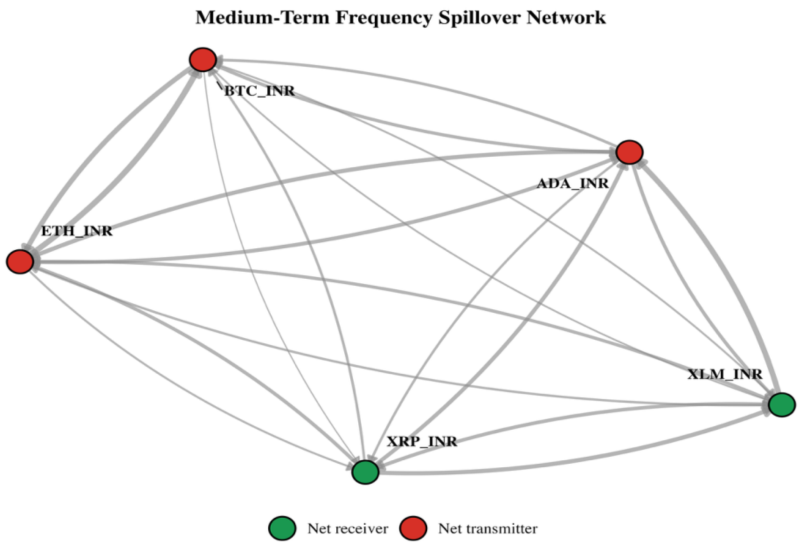
ETH_INR	2.63	**5.12**	1.99	1.39	1.25	**7.26**
ADA_INR	1.59	2.14	**5.17**	1.75	1.37	**6.85**
XLM_INR	1.20	1.74	2.49	**5.24**	1.89	**7.32**
XRP_INR	1.40	1.81	1.97	2.16	**7.16**	**7.33**
TO	**6.82**	**8.04**	**8.22**	**6.44**	**5.44**	
Net	**0.63**	**0.78**	**1.37**	**−0.88**	**−1.89**	
TCI (cTCI)						**6.99 (8.74)**

Source: Authors' computations using the Baruník and Křehlík (2018) frequency connectedness framework.

Note: Diagonal elements represent own variance shares, while off-diagonal elements indicate directional spillovers based on the generalized forecast error variance decomposition. FROM and TO denote directional spillovers received and transmitted, respectively. Net = TO − FROM. TCI denotes the Total Connectedness Index, and cTCI denotes the corrected Total Connectedness Index.

Table 5 presents the medium-term frequency connectedness among the selected cryptocurrencies. The results indicate a low level of interconnectedness, with a Total Connectedness Index (TCI) of 6.99% and a corrected Total Connectedness Index (cTCI) of 8.74%, indicating that medium-term return dynamics are driven primarily by asset-specific factors rather than cross-market spillovers. Cardano (TO = 8.22%) emerges as the largest transmitter of medium-term shocks, followed by Ethereum (TO = 8.04%) and Bitcoin (TO = 6.82%), whereas Ripple (TO = 5.44%) contributes the least to spillover transmission. The net spillover measures identify Cardano (Net = 1.37), Ethereum (Net = 0.78), and Bitcoin (Net = 0.63) as net transmitters, while Stellar (Net = −0.88) and Ripple (Net = −1.89) remain net receivers. Compared with short-term connectedness (TCI = 41.86%), the substantial decline in medium-term connectedness indicates weaker cross-market return transmission and greater dominance of cryptocurrency-specific factors. These findings suggest greater diversification opportunities for medium-term investors as the influence of market-wide spillovers diminishes.

Figure 6. Medium-Term Frequency Spillover Network among Selected Cryptocurrencies



Source: Authors' illustration based on the Baruník and Křehlík (2018) frequency connectedness framework.

Note: The figure presents the medium-term spillover network estimated using the Baruník and Křehlík (2018) frequency connectedness framework. Red nodes denote net transmitters, while green nodes denote net receivers.

Directed edges indicate the direction of spillover transmission, and edge widths are proportional to the magnitude of spillover effects.

Figure 6 illustrates the medium-term spillover network among the selected cryptocurrencies estimated using the Baruník and Křehlík (2018) frequency connectedness framework. The network depicts the direction and relative intensity of medium-term return spillovers, with red nodes representing net transmitters, green nodes representing net receivers, and edge thickness indicating spillover strength. Consistent with Table 5, Cardano (ADA), Ethereum (ETH), and Bitcoin (BTC) emerge as the principal net transmitters of medium-term shocks, while Stellar (XLM) and Ripple (XRP) function as net receivers. Compared with the short-term network, the thinner links indicate substantially weaker connectivity, consistent with the low Total Connectedness Index (TCI) of 6.99%. Overall, the network suggests that medium-term return dynamics are driven primarily by asset-specific factors rather than market-wide spillovers, indicating greater potential for portfolio diversification as cross-market return transmission weakens.

Long-Term Frequency Connectedness

Table 6. Long-Term Frequency Connectedness Matrix

Cryptocurrency	BTC_INR	ETH_INR	ADA_INR	XLM_INR	XRP_INR	FROM
BTC_INR	**1.93**	0.84	0.64	0.42	0.32	**2.22**
ETH_INR	1.01	**1.86**	0.73	0.52	0.46	**2.71**
ADA_INR	0.62	0.80	**1.85**	0.63	0.50	**2.54**
XLM_INR	0.48	0.69	0.96	**1.90**	0.73	**2.86**
XRP_INR	0.56	0.72	0.78	0.84	**2.70**	**2.90**
TO	**2.66**	**3.04**	**3.11**	**2.40**	**2.01**	
Net	**0.44**	**0.33**	**0.57**	**−0.45**	**−0.89**	
TCI (cTCI)						**2.65 (3.31)**

Source: Authors' computations using the Baruník and Křehlík (2018) frequency connectedness framework.

Note: Diagonal elements represent own variance shares, while off-diagonal elements indicate directional spillovers based on the generalized forecast error variance decomposition. FROM and TO denote directional spillovers received and transmitted, respectively. Net = TO − FROM. TCI denotes the Total Connectedness Index, and cTCI denotes the corrected Total Connectedness Index.

Table 6 reports the long-term frequency connectedness among the selected cryptocurrencies. The results indicate a very low level of interconnectedness, with a Total Connectedness Index (TCI) of 2.65% and a corrected Total Connectedness Index (cTCI) of 3.31%, indicating that long-term return dynamics are driven predominantly by asset-specific factors rather than cross-market spillovers. Cardano (TO = 3.11%) remains the largest transmitter of long-term shocks, followed by Ethereum (TO = 3.04%) and Bitcoin (TO = 2.66%), whereas Ripple (TO = 2.01%) contributes the least to spillover transmission. The net spillover measures identify Cardano (Net = 0.57), Bitcoin (Net = 0.44), and Ethereum (Net = 0.33) as net transmitters, while Stellar (Net = −0.45) and Ripple (Net = −0.89) remain net receivers. Compared with the short-term (TCI = 41.86%) and medium-term (TCI = 6.99%) results, the marked decline in long-term connectedness indicates that cross-market return spillovers weaken progressively as the investment horizon increases. These findings suggest greater long-term portfolio diversification opportunities, as market-wide spillover effects become increasingly limited and asset-specific factors dominate return dynamics.

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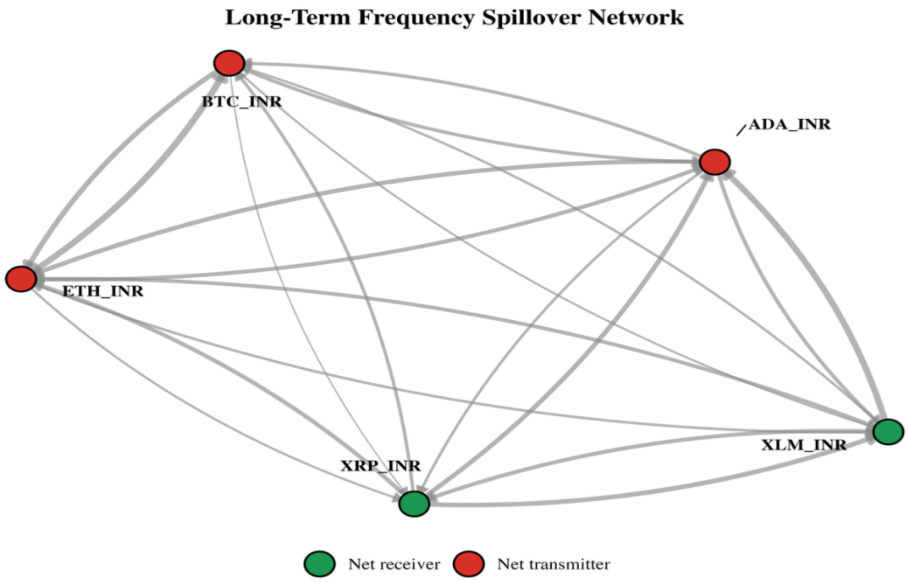
Figure 7. Long-Term Frequency Spillover Network



Source: Authors' illustration based on the Baruník and Křehlík (2018) frequency connectedness framework.

Note: Long-term frequency spillover network among BTC, ETH, ADA, XLM, and XRP in the Indian cryptocurrency market. Red nodes denote net transmitters of spillovers, while green nodes denote net receivers. Directed edges represent the direction of return spillovers, and edge thickness is proportional to the magnitude of spillover transmission.

Figure 7 illustrates the long-term spillover network among Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), Stellar (XLM), and Ripple (XRP) in the Indian cryptocurrency market based on the Baruník and Křehlík (2018) frequency connectedness framework. Compared with the short- and medium-term networks, the long-term network is considerably less dense, consistent with the low Total Connectedness Index (TCI) of 2.65%. Cardano (ADA), Bitcoin (BTC), and Ethereum (ETH) emerge as the principal net transmitters of long-term return spillovers, while Stellar (XLM) and Ripple (XRP) function as net receivers. The thinner links indicate that the intensity of return transmission declines substantially over longer investment horizons, suggesting that long-term return dynamics are driven primarily by asset-specific factors rather than persistent cross-market spillovers. Overall, the network indicates weak long-term connectedness and suggests greater potential for portfolio diversification over longer investment horizons.

Comparative Analysis Across Frequency Horizons

Table 7. Comparative Summary of Frequency Connectedness Measures

Measure	**Short-term**	**Medium-term**	**Long-term**
Total Connectedness Index (TCI, %)	41.86	6.99	2.65
Corrected TCI (cTCI, %)	52.33	8.74	3.31
Major net transmitters	ETH, ADA, XLM	ADA, ETH, BTC	ADA, BTC, ETH
Major net receivers	BTC, XRP	XLM, XRP	XLM, XRP

Source: Authors' calculations based on the Baruník and Křehlík (2018) frequency connectedness framework.

Table 7 compares the connectedness measures across the short-, medium-, and long-term investment horizons. The Total Connectedness Index (TCI) declines sharply from 41.86% in the short term to 6.99% in the medium term and 2.65% in the long term, while the corrected Total Connectedness Index (cTCI) follows a similar pattern, declining from 52.33% to 8.74% and 3.31%, respectively. These results indicate that return spillovers are concentrated in the short term and weaken substantially as the investment horizon increases. Ethereum (ETH) emerges as the strongest net transmitter in the short term, while Cardano (ADA) becomes the leading net transmitter over the medium and long terms. Bitcoin (BTC) shifts from a net receiver in the short term to a net transmitter in the medium and long terms, whereas Stellar (XLM) and Ripple (XRP) remain net receivers across the investment horizons. Overall, the findings demonstrate that connectedness in the Indian cryptocurrency market is strongly frequency dependent, with stronger short-term interdependence and greater potential for portfolio diversification over medium- and long-term horizons as cross-market return transmission declines.

DISCUSSION

The findings demonstrate that connectedness in the Indian cryptocurrency market is strongly frequency dependent. Although the overall results indicate moderate connectedness, the frequency decomposition reveals that return spillovers are concentrated in the short term and decline substantially over medium- and long-term investment horizons. This indicates that cross-market return transmission is considerably stronger at shorter investment horizons, whereas the contribution of cross-market spillovers becomes weaker as the investment horizon increases. These findings are consistent with the frequency connectedness framework of Baruník and Křehlík (2018) and previous studies reporting stronger spillovers at higher frequencies (Mensi et al., 2021; Nyakurukwa & Seetharam, 2023; Polat & Kabakçı Günay, 2021).

The relatively high short-term connectedness indicates stronger cross-market transmission over shorter investment horizons. As the investment horizon lengthens, spillover intensity decreases markedly, suggesting that return dynamics become increasingly influenced by cryptocurrency-specific factors rather than cross-market interactions. Similar frequency-dependent patterns have been documented by Fousekis and Tzaferi (2021), Hanif et al. (2023), Long et al. (2024), and Mo et al. (2022).

Among the selected cryptocurrencies, Ethereum (ETH) emerges as the strongest net transmitter of return spillovers in the short term, while Cardano (ADA) becomes the leading net transmitter over the medium and long terms. Ethereum also maintains a significant transmitting role across the different investment horizons. In contrast, Ripple (XRP) consistently functions as the principal net receiver, whereas Bitcoin (BTC) shifts from a net receiver in the short term to a net transmitter over the medium and long terms. These findings indicate that return spillover transmission is heterogeneous across cryptocurrencies and varies across investment horizons, supporting the evidence reported by Assaf et al. (2024), Esparcia et al. (2024), and Katsiampa et al. (2022).

From an investment perspective, the results suggest that diversification opportunities may be relatively limited over short investment horizons because of stronger connectedness and cross-market return transmission. However, the substantial decline in connectedness from 41.86% in the short term to 6.99% in the medium term and 2.65% in the long term indicates greater potential for portfolio diversification over longer holding periods. For policymakers and regulators, the findings highlight the importance of monitoring periods of heightened short-term market activity, when return spillovers are more pronounced across cryptocurrencies. Overall, the results reinforce recent evidence that portfolio risk, hedging effectiveness, and financial stability depend not only on the magnitude of connectedness but also on its variation across investment horizons (Adelopo & Luo, 2025; Marco et al., 2023). The study demonstrates that frequency-domain connectedness analysis provides richer insights into return transmission than aggregate connectedness measures alone, offering valuable implications for portfolio management, risk assessment, and regulatory decision-making in the Indian cryptocurrency market.

CONCLUSION

This study examined the frequency-dependent return connectedness among Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), Stellar (XLM), and Ripple (XRP) in the Indian cryptocurrency market using daily INR-denominated prices from March 2018 to December 2025. Employing the Baruník and Křehlík (2018) frequency connectedness framework enabled the decomposition of return spillovers across short-, medium-, and long-term investment horizons.

The findings reveal moderate overall market connectedness, with return spillovers concentrated primarily in the short term and declining substantially over medium- and long-term horizons. Ethereum (ETH) emerges as the strongest net transmitter of return spillovers in the short term, while Cardano (ADA) becomes the leading net transmitter over the medium and long terms**.** In contrast, Ripple (XRP) remains the principal net receiver, whereas Bitcoin (BTC) shifts from a net receiver in the short term to a net transmitter over the medium and long terms. These results demonstrate that both the magnitude and direction of return spillovers vary across cryptocurrencies and investment horizons.

The study contributes to the literature by providing frequency-domain evidence from the Indian cryptocurrency market, an emerging market that has received comparatively limited attention in previous connectedness research. The findings highlight the importance of considering frequency-specific dynamics when evaluating market connectedness, systemic risk, and return transmission.

From a practical perspective, the results suggest that diversification opportunities may be relatively limited over short investment horizons because of stronger market connectedness, whereas weaker medium- and long-term connectedness offers greater potential for portfolio diversification. The identification of dominant transmitters and receivers of return spillovers also provides useful insights for portfolio management, risk assessment, and regulatory monitoring.

Overall, the study demonstrates that return connectedness in the Indian cryptocurrency market is strongly frequency dependent. Understanding how return spillovers evolve across investment horizons provides valuable insights for investors, portfolio managers, and policymakers seeking to manage risk and improve decision-making in increasingly interconnected digital asset markets.

Limitations And Future Research

This study has several limitations. First, the analysis is limited to five major cryptocurrencies traded in the Indian market and may not fully capture the connectedness of the broader cryptocurrency ecosystem. Second, the analysis uses daily data, which may not capture intraday spillover dynamics and higher-frequency market interactions. Third, the study employs only the Baruník and Křehlík (2018) frequency connectedness framework; therefore, the results may differ when alternative connectedness methodologies are applied.

Future research may extend the analysis by incorporating a broader range of cryptocurrencies, including stablecoins and decentralized finance (DeFi) assets, using higher-frequency data, comparing developed and emerging cryptocurrency markets, and applying alternative connectedness frameworks to assess the robustness of the findings. Such extensions could provide a more comprehensive understanding of return transmission and market connectedness across evolving digital asset markets.

Declaration of Conflicting Interests

The author declares that there is no potential conflict of interest with respect to the research, authorship, and publication of this article.

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Data Availability Statement

The data employed in this study were sourced from publicly accessible financial databases, and are available from the corresponding author upon reasonable request.

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