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Volatility Spillovers and Correlation Dynamics between Bitcoin and Indian Equity Index: Evidence from DCC-GARCH and Diebold-Yilmaz Analysis

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Abstract
This study investigates the volatility dynamics, return causality, and connectedness between Bitcoin (BTC-INR) and the Indian equity market index (Nifty 50) using daily data from April 2015 to March 2025. Comprehensive econometric framework such as descriptive statistics, stationarity, and causality tests, GARCH (1,1) modelling, Dynamic Conditional Correlation (DCC-GARCH), and the Diebold–Yilmaz spillover index is employed, which provides insights into the relationship between cryptocurrency and equity markets in India. The results indicate that BTC and Nifty 50 returns are stationary and exhibit non-normal distributions with volatility clustering. Granger causality tests reveal unidirectional causality from BTC to Nifty 50, suggesting the predictive influence of cryptocurrency on Indian equities. The GARCH (1,1) estimates show that BTC volatility is more sensitive to new shocks, while Nifty 50 volatility is more persistent, confirming distinct volatility structures across the two assets. DCC-GARCH results demonstrate that correlations are generally weak and time-varying, with temporary increases during global financial stress such as the COVID-19 pandemic. The spillover analysis reports a very low Total Connectedness Index (0.52%), confirming minimal return transmission between the two markets. These outcomes support the hypothesis that Bitcoin (BTC-INR) and Nifty 50 Index exhibit weak correlation and limited volatility spillovers under normal conditions, with short-lived co-movements emerging during systemic events. The findings indicate that Bitcoin might serve as a viable diversification tool in Indian portfolios, and its limited connectedness indicates toward little systemic risk to the domestic financial system.

Keywords: Bitcoin (BTC), Nifty 50, Volatility Dynamics, GARCH (1,1), DCC-GARCH, Diebold–Yilmaz Spillover Index, Portfolio Diversification

1. Introduction

Financial markets have become increasingly interconnected where asset prices respond rapidly to external shocks, policy changes, and macroeconomic developments. This heightened sensitivity indicates how important it is for investors and policymakers to understand how volatility is transmitted across markets and how correlations between assets evolve. The existence or absence of volatility spillovers affects portfolio diversification and risk management. Strong cross-market linkages may

reduce diversification benefits, whereas weak or segmented relationships may enhance them (Diebold & Yilmaz, 2012a).

Global financial markets have also undergone a rapid transformation in recent years, with the rise of cryptocurrencies, most notably Bitcoin (BTC) (Corbet et al., 2019). As the first and most widely traded digital asset, BTC has attracted global attention from investors, regulators, and academics due to its extreme volatility, speculative behaviour, and potential nature as an alternative asset class (Dyhrberg, 2016). In contrast, traditional equity markets, such as India's Nifty 50 index is central to the financial system, reflecting the performance of the country's largest and most liquid firms. Understanding the relationship between cryptocurrency and equity markets is increasingly important, providing insights into risk transmission, diversification opportunities, and financial stability (Corbet et al., 2018). This issue is particularly relevant for India, given the growing adoption of digital assets and ongoing regulatory debates regarding their place in the financial system. While global evidence generally suggests that Bitcoin is only weakly correlated with traditional markets, uncertain timeline such as the COVID-19 pandemic has influenced temporary increase in co-movement and volatility spillovers (Yarovaya et al., 2021). This raises important questions about whether BTC can serve as a hedge or diversifier against risks in the Indian equity market (Kalyvas et al., 2020).

Advanced econometric frameworks are employed to analyse these dynamics. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1986) captures volatility clustering within individual time series, accounting for time-varying volatility driven by past shocks and persistence. Extending this, the Dynamic Conditional Correlation–GARCH (DCC-GARCH) model (Engle, 2002) provides a multivariate framework that measures how conditional correlations between assets evolve. Unlike static correlations, DCC-GARCH captures shifts in dependence structures across different market conditions, highlighting periods when assets move more closely together, particularly during crises (Ji et al., 2019). The Diebold–Yilmaz spillover index (Diebold & Yilmaz, 2012a) quantifies volatility transmission across markets by decomposing forecast error variances in a VAR framework. Together, these measures allow for a comprehensive assessment of volatility persistence, time-varying correlations, and cross-market spillovers.

Accordingly, this study examines the dynamic relationship between Bitcoin (BTC-INR) and Nifty 50 Index returns over 2015–2025 using GARCH modelling, DCC-GARCH correlation analysis, and the Diebold–Yilmaz spillover index. We hypothesize that the Indian equity market (represented by Nifty 50) and the cryptocurrency market (represented by BTC-INR) exhibit a weakly correlated relationship under normal market conditions, with minimal volatility spillovers between the two. However, temporary co-movements or spillovers may emerge during global or systemic events (e.g., COVID-19) (Akhtaruzzaman et al., 2021). Hence, BTC and Indian equity could serve as effective portfolio diversification and risk hedging instruments (Bouri et al., 2017).

This study contributes to the literature by focusing on an emerging market context, employing robust econometric models to capture volatility persistence and spillover dynamics, and offering practical implications for investors and policymakers regarding diversification strategies and systemic risk management.

2. Research Methodology

2.1. Data and Sample

This study investigates the volatility spillovers and correlation dynamics between Bitcoin (BTC-INR)

and the Nifty 50 Index of the Indian equity market. Daily closing prices are obtained from Yahoo Finance, covering the period from April 2015 to March 2025. Since Bitcoin (BTC-INR) trades continuously while Nifty 50 Index operates only on weekdays, weekend values are removed from the Bitcoin series to ensure alignment. The two datasets are merged on common trading days, resulting in a final sample of 2,459 daily observations for each return series.

Logarithmic returns are computed as the first difference of the natural logarithm of prices:

$$R_t = ln(P_t) - \ln(P_{t-1})$$

here R_t denotes the log return and P_t the closing price at time t.

To ensure robustness, both raw return series and winsorized returns (1st–99th percentile) are analysed. Winsorization trims extreme minimum and maximum values (BTC: min −0.461 to −0.130, max 0.226 to 0.110; Nifty 50: min −0.139 to −0.027, max 0.084 to 0.025), while preserving central tendencies such as mean and median. Standard deviations decrease modestly after winsorization (BTC: 0.042 to 0.039; Nifty 50: 0.0105 to 0.0089), indicating reduced volatility. The Bitcoin (BTC-INR) and Nifty 50 Index correlation weakens from 0.058 in the raw data to 0.023 in the winsorized data, suggesting that extreme BTC shocks contributed marginally to cross-market dependence.

All statistical analysis, data preprocessing, and modelling are conducted in the R Studio language using appropriate econometric packages.

2.2. Analytical Techniques

2.2.1. Descriptive Statistics and Correlation

Descriptive statistics such as mean, standard deviation, skewness, kurtosis, and the Jarque-Bera test are reported to characterize the distributional properties of the returns. In addition to static correlation, rolling correlations with 30-day windows are computed to capture time-varying dependence between Bitcoin (BTC-INR) and Nifty 50 Index.

2.2.2. Granger Causality Test

Granger causality tests are used to determine if Bitcoin (BTC-INR) and Nifty 50 Index have a directional predictive relationship. The tests evaluate whether lagged BTC returns significantly improve the prediction of NIFTY returns and vice versa.

2.2.3. Stationarity Tests

The stationarity of the Bitcoin (BTC-INR) and Nifty 50 Index return series is assessed using the Augmented Dickey-Fuller (ADF) test. Stationarity is a necessary condition for GARCH models as it ensures constant statistical properties over time.

2.2.4. Univariate Volatility Modelling – GARCH (1,1)

Conditional volatility is modelled using GARCH (1,1) specifications for each return series, the GARCH (1,1) specification is applied:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

The ARCH term (α) captures sensitivity to new shocks, while the GARCH term (β) reflects persistence of volatility. Diagnostic tests including the Ljung–Box test (for residual autocorrelation) and the ARCH LM test (for remaining heteroskedasticity) are used to evaluate model adequacy (Bollerslev et al., 1992).

2.2.5. Dynamic Conditional Correlation (DCC-GARCH)

To examine evolving linkages between Bitcoin (BTC-INR) and Nifty 50 Index, the DCC-GARCH model is employed. t extends the univariate GARCH to a multivariate framework, allowing conditional correlations to vary dynamically over time:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha(u_{t-1}u'_{t-1}) + \beta Q_{t-1}$$

where Q_t is the conditional correlation matrix, $\bar{Q}$ is the unconditional correlation, and u_t are standardized returns. This framework captures both short-term responses to shocks and persistence in correlation structures.

2.2.6. Spillover Analysis – Diebold–Yilmaz Framework

To quantify volatility spillovers, the Diebold–Yilmaz (2012) spillover index is applied (Diebold & Yilmaz, 2012b). A VAR (1) model is estimated, and the forecast error variance decomposition (FEVD) with a 10-day horizon is computed:

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

This generates a connectedness matrix, showing own- and cross-market contributions, and an overall spillover index, measuring the total degree of market connectedness.

To assess return spillovers between Bitcoin (BTC-INR) and Nifty 50 Index, we compute the Total Connectedness Index (TCI). The TCI is derived from the forecast error variance decomposition (FEVD) of a VAR model and measures the share of forecast error variance explained by cross-market shocks. Formally, it is defined as:

$$TCI = \frac{\sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N}\theta_{ij}}{N} \times 100$$

where θ_{ij} denotes the proportion of the H-step-ahead forecast error variance of variable i attributable to innovations in variable j, and N is the number of variables in the system(Magner & Sanhueza, 2025).

3. Empirical Data Analysis

3.1. Descriptive Statistics

The descriptive statistics calculates daily log returns which shows notable differences in distributional properties reported in **Table 1**. BTC exhibits a higher mean return (0.0023) compared to Nifty 50 (0.0004), but also substantially higher volatility (standard deviation of 0.042 versus 0.010). Both series are negatively skewed, with Nifty 50 showing a stronger left skew, indicating greater probability of large negative returns. The kurtosis values (12.95 for BTC, 23.72 for Nifty 50) suggest fat-tailed distributions relative to normality. The Jarque-Bera test strongly rejects normality for both series. These results are consistent with stylized facts of financial time series, highlighting volatility clustering, heavy tails, and asymmetry.

Table 1: Descriptive Statistics of Bitcoin (BTC-INR) & NIFTY 50 Index
(Values based on daily returns, 2015–2025)

Statistics	Bitcoin (INR)	NIFTY 50
Mean	0.00227	0.00041
Median	0.00157	0.00066
Min	-0.4612	-0.1390
Max	0.2257	0.0840
Std Dev	0.04216	0.01050
Skewness	-0.6713	-1.4162

Kurtosis	12.95	23.72
Jarque-Bera	10327.94	44801.03
Observations	2459	2459

3.2. Stationarity and Causality

The Augmented Dickey-Fuller (ADF) test confirms that both Bitcoin (BTC-INR) and Nifty 50 Index return series are stationary at the 1% significance level, ensuring suitability for volatility Modelling. Granger causality test results (see **Table 2**) indicate unidirectional causality: BTC returns significantly Granger-cause Nifty 50 returns (F = 6.51, p = 0.0015), while Nifty 50 does not Granger-cause BTC. The data suggests that movements in BTC contain predictive information for Indian equities, but not vice versa.

Table 2: Granger Causality Test Result

Null Hypothesis (Ho)	**F-Statistic**	**p-value**
BTC does **not** Granger-cause NIFTY 50	6.5135	0.001509
NIFTY 50 does **not** Granger-cause BTC	1.3025	0.272

To further examine autocorrelation structures, the ACF and PACF plots for BTC and Nifty 50 returns are shown in **Figure 1**. Both return series exhibit rapidly decaying autocorrelations, supporting the stationarity findings from the ADF test. These patterns justify the use of GARCH-type models for capturing volatility clustering.

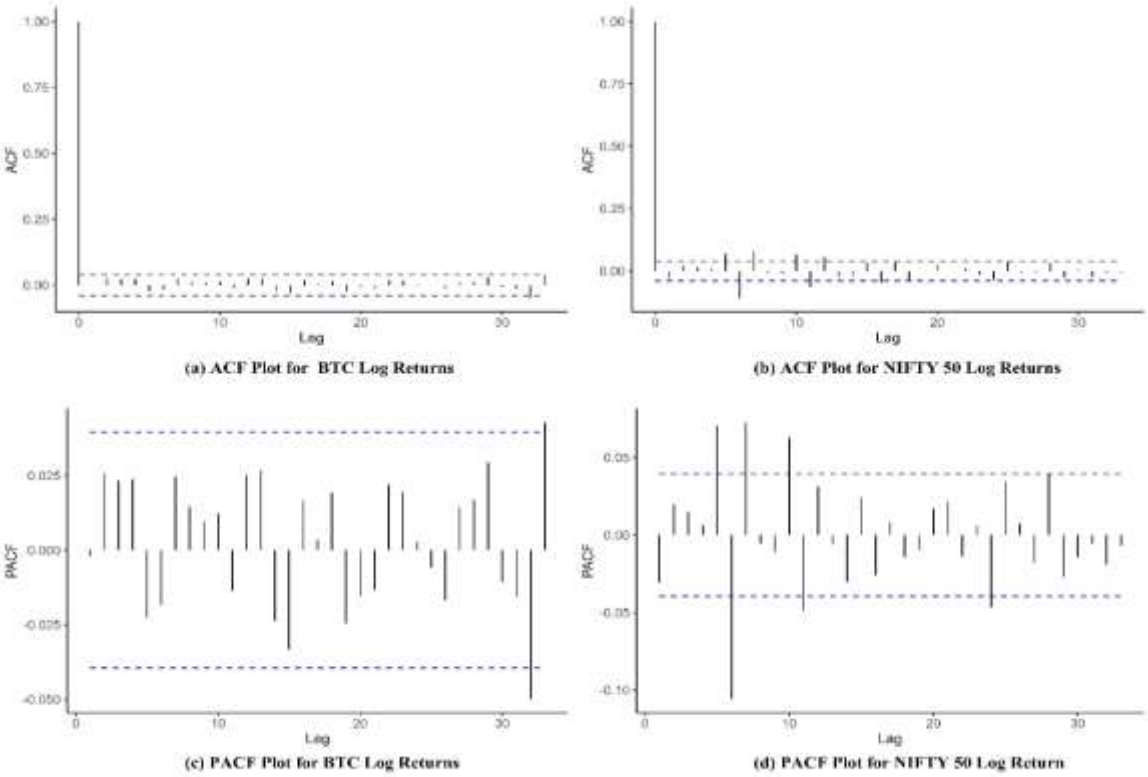

Figure 1: ACF and PACF Plots of BTC and NIFTY Log Returns

3.3. Correlation Analysis

The unconditional correlation between Bitcoin (BTC-INR) and Nifty 50 Index returns is close to zero (0.022), indicating weak static dependence. However, 30-day rolling correlation estimates show that dependence is time-varying, fluctuating between slightly negative and moderately positive levels. As illustrated in **Figure 2,** Temporary spikes are observed during global turbulence such as the COVID-19 pandemic (2020) and market corrections in 2022, suggesting that cross-market co-movement intensifies during periods of increased uncertainty.

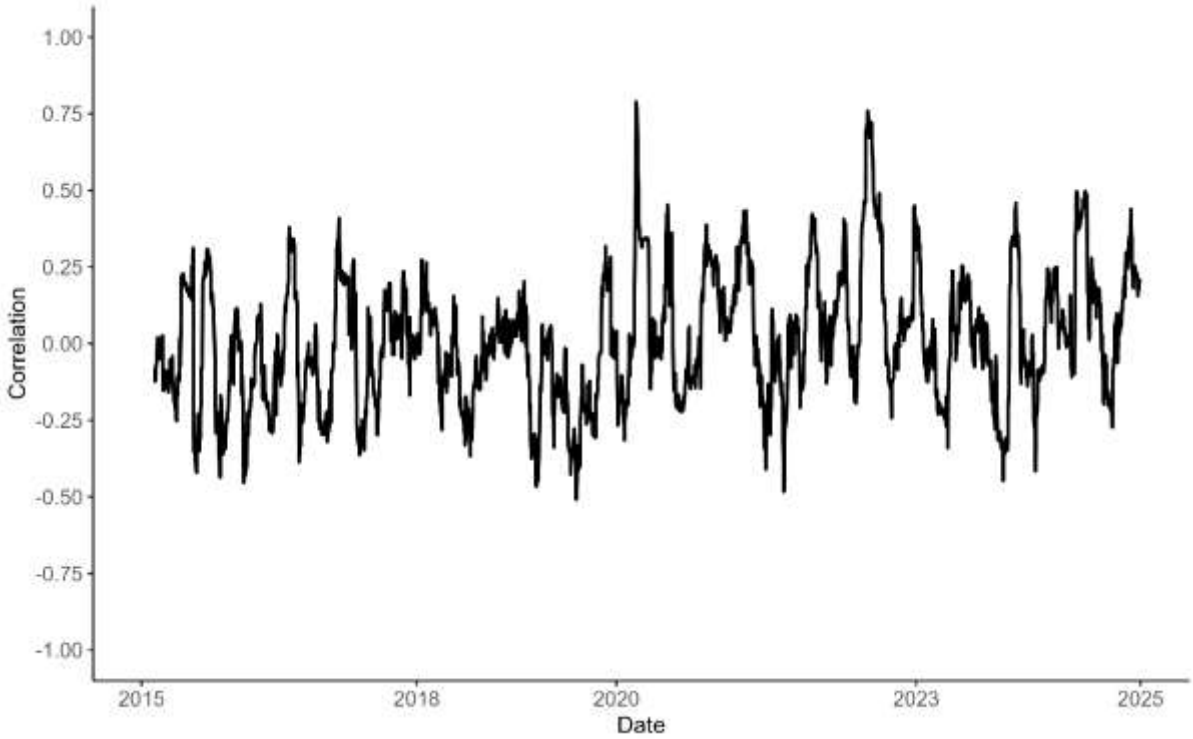

Figure 2: 30 Days Rolling Correlation of Bitcoin (BTC-INR) & NIFTY 50

3.4. Volatility Dynamics: GARCH (1,1) Results

The univariate GARCH (1,1) estimates in **Table 3**, reveal distinct volatility structures for Bitcoin (BTC-INR) and Nifty 50 Index. BTC ARCH parameter ($\alpha_1 = 0.137$) exceeds NIFTY's ($\alpha_1 = 0.111$), indicating stronger sensitivity to new shocks. Conversely, Nifty 50 GARCH parameter ($\beta_1 = 0.860$) is higher than BTC ($\beta_1 = 0.810$), implying greater persistence of volatility. In both cases, the sum of ARCH and GARCH terms is close to unity (0.97 for Nifty 50, 0.95 for BTC), confirming long memory and volatility clustering. Diagnostic tests show no remaining ARCH effects, validating model adequacy. Collectively, these results suggest that BTC exhibits higher short-term volatility and reacts more sharply to shocks, while Nifty 50 displays more stable but persistent volatility patterns.

Table 3: Univariate Volatility Modelling – GARCH (1,1) Estimates

Parameter	NIFTY 50 (Return Series)	BTC (Return Series)
Mean Equation		
μ (Mean return)	0.00071 ***	0.00205 **
	(0.0002)	(0.0010)

Variance Equation		
ω (Omega)	0.000003	0.000118 **
	(0.00001)	(0.00005)
α_1 (ARCH)	0.1109 ***	0.1370 ***
	(0.018)	(0.025)
β_1 (GARCH)	0.8595 ***	0.8096 ***
	(0.022)	(0.030)
$\alpha_1 + \beta_1$	0.9704	0.9466
Model Fit		
Log-Likelihood	8144.7	4462.2
Diagnostics		
Ljung–Box (p-value)	> 0.05	> 0.05
ARCH LM Test (p-value)	> 0.05	> 0.05
*(Notes: Standard errors in parentheses. Significance levels: ***1%, **5%)		

Figures 3 presents the conditional volatility estimates of Bitcoin (BTC-INR) and Nifty 50 Index returns obtained from the GARCH (1,1) models. (a) BTC Conditional Volatility shows substantially higher and more volatile fluctuations, with frequent spikes indicating sensitivity to sudden market shocks and news-driven events. Whereas, (b) Nifty 50 Conditional Volatility exhibits relatively lower and smoother volatility, though notable increases appear during global stress periods, particularly around early 2020. Both assets display clear evidence of volatility clustering, consistent with the GARCH framework, but BTC's volatility is characterized by stronger short-term bursts, whereas Nifty 50 volatility is more persistent yet less extreme in magnitude.

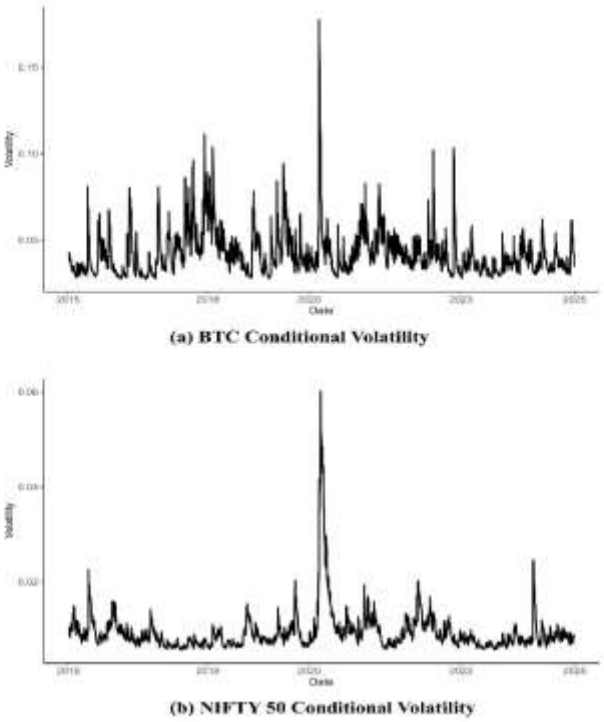

Figure 3: GARCH (1,1) - Conditional Volatility of Bitcoin (BTC-INR) & NIFTY 50

To capture time-varying correlations between the two markets, the DCC-GARCH framework was employed. The persistence parameter is highly significant, showing that once BTC and Nifty 50 correlations shift, they remain stable for extended periods. The shock effect is weak and insignificant, suggesting that short-term shocks do not substantially influence co-movements. The dynamic correlation plot (**Figure 4**) demonstrates that overall correlations are low, but temporary spikes occur during global financial stress episodes.

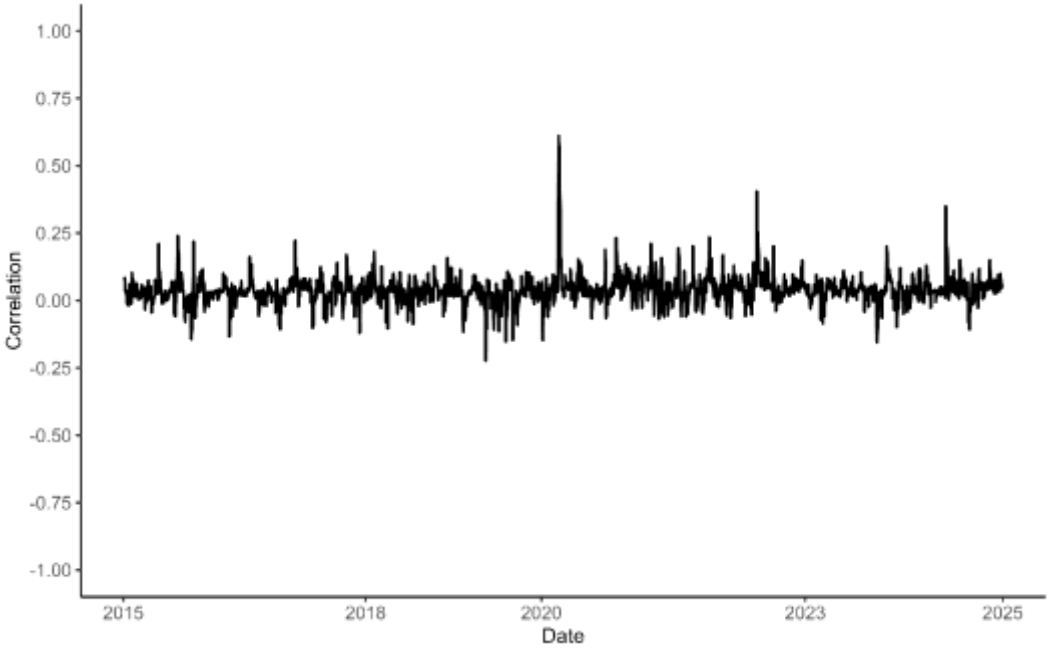

Figure 4: DCC-GARCH - Dynamic Correlation between Bitcoin (BTC-INR) & NIFTY 50

3.5. Diebold–Yilmaz Spillover Index

The connectedness matrix in **Table 4.** summarizes the spillover effects between Bitcoin (BTC-INR) and Nifty 50 Index using the Diebold-Yilmaz (2012) methodology. The diagonal elements (99.59% for BTC and 99.37% for Nifty 50) indicate that both markets are largely driven by their own shocks, reflecting high levels of market-specific dynamics. The off-diagonal elements capture cross-market spillovers where BTC contributes only 0.41% to Nifty 50 return variation, while Nifty 50 contributes 0.63% to BTC's return variation. The Total Connectedness Index (TCI) is **0.52%**, suggesting extremely weak return spillovers between the two markets. This result implies that BTC and Nifty 50 remain relatively segmented in terms of volatility transmission, with minimal evidence of return connectedness during the sample period.

Table 4: Connectedness Matrix – Diebold–Yilmaz Spillover Index

	BTC Return	**NIFTY 50 Return**	**FROM**
BTC Return	99.59	0.41	0.20
NIFTY 50 Return	0.63	99.37	0.31
TO	0.31	0.20	
Total Connectedness Index (TCI)			**0.52**

3.6. Robustness Check: Outlier Treatment

Financial return series often display extreme values due to sudden shocks such as crashes, rallies, or policy changes. Since these events are important features of financial markets, the main analysis in this paper is based on the raw return series. However, to verify that the findings are not disproportionately driven by extreme observations, we performed a robustness check by winsorizing returns at the 1st and 99th percentiles. Winsorization caps the tails of the distribution without altering the number of observations.

Table 5, presents the summary statistics of BTC and NIFTY returns before and after winsorization. For both series, the mean and median remain almost unchanged, while the minimum and maximum values are considerably closer after winsorization, reflecting the trimming of extremes. Standard deviations are lower in the winsorized series, indicating reduced volatility. Importantly, the BTC and Nifty 50 correlation decreases from 0.058 in the raw data to 0.023 in the winsorized data, suggesting that some of the observed dependence was driven by extreme BTC movements. Overall, these checks confirm that the core results are robust and not sensitive to outliers.

Table 5: Raw vs Winsorized Returns – BTC and NIFTY 50

Statistic	BTC (Raw)	BTC (Winsorized)	NIFTY 50 (Raw)	NIFTY 50 (Winsorized)
Min	-0.4612	-0.1304	-0.1390	-0.0270
1st Quartile (Q1)	-0.0145	-0.0145	-0.0044	-0.0044
Median	0.0016	0.0016	0.0007	0.0007
Mean	0.0023	0.0023	0.0004	0.0005
3rd Quartile (Q3)	0.0205	0.0205	0.0060	0.0060
Max	0.2257	0.1101	0.0840	0.0248
Standard Deviation (SD)	0.0422	0.0385	0.0105	0.0089
Correlation (BTC~NIFTY)	0.0581	0.0227	—	—

4. Conclusion

This study analysed the volatility dynamics, return causality, and connectedness between Bitcoin (BTC-INR) and the Indian equity market index (Nifty 50) using daily data from April 2015 to March 2025. Drawing on the results of descriptive statistics, causality tests, univariate GARCH models, the DCC-GARCH framework, and the Diebold–Yilmaz spillover index, offering a comprehensive view of the interplay between cryptocurrency and equity in an emerging market context.

The results show that both Bitcoin (BTC-INR) and Nifty 50 Index return deviate from normality, exhibiting skewness, excess kurtosis, and volatility clustering, in line with the stylized facts of financial time series. Stationarity of the return series is confirmed by the ADF test, validating the use of GARCH model. Granger causality tests indicate a unidirectional relationship from BTC to Nifty 50, implying that cryptocurrency movements contain predictive information for Indian equity market, while the reverse effect is absent.

The GARCH (1,1) results highlight distinct volatility dynamics across the two markets. BTC volatility reacts strongly to immediate shocks, reflecting its higher short-term risk exposure, whereas Nifty 50 volatility is more persistent and decays more slowly, consistent with a more stable but enduring risk profile. The DCC-GARCH framework further reveals that correlations between BTC and Nifty 50 are weak and time-varying, remaining close to zero under normal conditions but rising modestly during global financial stress episodes, such as the COVID-19 pandemic. This indicates limited integration between the two markets, with temporary co-movements emerging only in times of crisis. The Diebold–Yilmaz spillover analysis provides further evidence of weak connectedness, reporting a very low Total Connectedness Index of just 0.52 percent. BTC emerges as a net transmitter of shocks and NIFTY as a net receiver, although the magnitudes are negligible and economically insignificant.

The evidence validates the hypothesis that BTC and Indian equity market is weakly correlated under normal conditions, with minimal volatility spillovers between them. While temporary increases in correlation and spillover occur during systemic shocks, such as the COVID-19 crisis, these are short-lived. For investors, this suggests that BTC may serve as a useful portfolio diversifier in stable periods but cannot be relied upon as a safe haven asset during crises. For policymakers, the weak connectedness indicates that Bitcoin currently poses little systemic risk to the Indian financial system, although continued monitoring remains important given the growing adoption of digital assets in India.

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