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Do Stablecoin Depegs Matter for Equities? Insights from NIFTY Volatility Modelling

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Abstract

Stablecoins constitute the principal settlement instrument of cryptocurrency markets, raising the question of whether a broken peg conveys information to equity markets beyond the crypto sector. Building on multiple studies that have modelled cryptocurrency volatility spillovers into equity markets, this study focuses specifically on whether depegging events represent a distinct transmission channel of risk and information by addressing that question in the Indian context. Employing 1,478 daily observations on the NIFTY 50 index between 31 December 2018 and 31 December 2024, a continuous measure of downside peg deviation is constructed for Tether and USD Coin. As cryptocurrency markets trade continuously whereas the National Stock Exchange does not, the measure records the maximum deviation over the calendar interval since the preceding NSE close and enters the specification with a one-day lag. Conditional volatility is modelled using an exponential GARCH (EGARCH) specification under a Student's t density, which is preferred to symmetric GARCH and threshold GARCH on the Akaike, Schwarz and Hannan-Quinn criteria. The asymmetry parameter is negative and significant at the 1% level (γ = -0.107 and -0.124), indicating that adverse innovations raise Indian equity volatility by more than favourable innovations of equal magnitude, while persistence is high but stationary (β = 0.964 and 0.942). Depeg intensity is statistically insignificant in the baseline specification (p = .380) and reverses sign upon inclusion of a dummy variable for the March-April 2020 market disruption (p = .789). Lagged Bitcoin returns, by contrast, significantly predict next-day NIFTY 50 returns (p < .001). Transmission from cryptocurrency markets to Indian equities therefore operated through returns rather than through stablecoin-specific volatility.

***Keywords**: Stablecoin Depegging, EGARCH, Volatility Spillover, NIFTY 50, Cryptocurrency.*

Introduction

A dollar-pegged stablecoin is designed to maintain parity with the United States dollar. Departure from that parity signals a deterioration in the quality of the underlying collateral, a failure of the arbitrage mechanism that restores the price to par, or an erosion of holder confidence. (Lyons & Viswanath-Natraj, 2022) demonstrate that peg stability depends upon the design of the arbitrage mechanism rather than upon issuance policy, and that algorithmic coins lacking full collateralisation possess no reliable restoring mechanism once they trade at a discount. Subsequent episodes establish that such failures are not contained within a single instrument: the Terra-Luna collapse of May 2022 (Briola et al., 2022) and the March 2023 failure of Silicon Valley Bank, which displaced USDC, DAI, FRAX and USDD from parity simultaneously (Diop & Sanhaji, 2024), both propagated across the sector.

If a depeg constitutes public information regarding systemic stress within the cryptocurrency sector, then under the semi-strong form of the efficient markets hypothesis (Fama, 1970) it should be incorporated into the price of any asset whose holders are exposed to that stress. Because the information concerns risk rather than expected cash flows, the appropriate locus of investigation is the second moment. Indian equities hold no claim upon stablecoin reserves; what a depeg may plausibly revise is the perceived riskiness of crypto-linked wealth, and such a revision would manifest as a shift in conditional variance rather than in the conditional mean.

India constitutes an informative setting for this test. Retail participation in cryptocurrency assets expanded rapidly across the sample period while the regulatory position remained unsettled, and since the National Stock Exchange closes at 15:30 Indian Standard Time whilst cryptocurrency markets trade continuously, any transmission must necessarily arrive with a lag. (Thomas, 2024) identifies volatility linkages between Bitcoin and the major Indian indices that are demonstrable but short-lived, whereas (Corbet et al., 2018) report that cryptocurrencies remain relatively isolated from conventional assets.

The extant stablecoin literature terminates at the boundary of the cryptocurrency sector, whilst the literature on crypto-equity transmission employs Bitcoin or a broad cryptocurrency index rather than a stablecoin-specific measure and the present study connects the two.

Objectives

This study examines whether stablecoin depegging generates volatility spillovers in the Indian equity market, taking the NIFTY 50 index of the National Stock Exchange as the receiving market. Four specific objectives follow. The first is to characterise the distributional and dynamic properties of NIFTY 50 daily returns over the period 2018-2024 and to establish whether GARCH-family modelling is warranted. The second is to construct a depeg measure that distinguishes genuine break-the-buck episodes from early-market pricing noise and that accommodates the divergence between continuous cryptocurrency trading and the NSE calendar. The third is to test whether lagged depeg intensity contributes incremental explanatory power to the conditional variance of NIFTY 50 returns once asymmetry, persistence and the pandemic-period disruption have been accounted for. The fourth is to determine whether cryptocurrency markets reach Indian equities through an alternative channel, specifically the conditional mean.

Hypotheses

Four hypotheses are tested, each corresponding to a parameter reported by the estimated specifications.

H1: Negative innovations raise the conditional variance of NIFTY 50 returns by more than positive innovations of equal magnitude ($\gamma < 0$). Such asymmetry follows from the leverage argument of (Black, 1976) and the volatility feedback mechanism of (Campbell & Hentschel, 1992), and motivates the estimation of (Nelson, 1991) and (Glosten et al., 1993) alongside the symmetric benchmark.

H2: Lagged stablecoin depeg intensity raises the conditional variance of NIFTY 50 returns ($\theta > 0$). This constitutes the central test and follows from the informational argument advanced above.

H3: Lagged Bitcoin returns assist in predicting NIFTY 50 returns in the conditional mean ($\delta > 0$). (Thomas, 2024) supports this expectation for India, whereas (Corbet et al., 2018) imply the contrary, so the prediction is not a foregone conclusion.

H4: The conditional distribution of NIFTY 50 returns exhibits heavier tails than the Gaussian, such that a Student’s t density provides superior fit (Mandelbrot, 1963).

Literature Review

- **Stablecoin Stability and the Mechanics of a Depeg**

The stablecoin literature has converged upon a reasonably clear account of why pegs fail. (Lyons & Viswanath-Natraj, 2022) locate stability in arbitrage access, demonstrating that peg deviations contracted once arbitrage of Tether became less costly, and that algorithmic designs lacking full collateral possess no equivalent restoring force at a discount. (Ahmed et al., 2024) provide the underlying theory by modelling coin holders as participants in a coordination game. In their formulation the informational quality of reserve assets determines which game is played: where the volatility of reserves is unknown, convertibility at par withstands small shocks but fails under a large negative public shock to reserve values. Disclosure is shown to operate in both directions, reducing run risk where holders hold favourable priors regarding reserve quality and increasing it where they do not.

The empirical evidence accords with this account. (Briola et al., 2022) reconstruct the Terra-Luna failure of May 2022 and attribute it to the project's dependence upon the Anchor protocol. (Diop et al., 2024) document the March 2023 cascade across four dollar-pegged coins following the failure of Silicon Valley Bank, with USDC most exposed owing to Circle's reserve holdings at that institution. (Jarno & Kołodziejczyk, 2021) approach the question differently, comparing realised volatility across twenty coins grouped by design, and establish that tokenised funds, collateralised coins and algorithmic coins do not deliver equivalent degrees of price stability. (Baur & Hoang, 2020) demonstrate that certain stablecoins function as a safe haven against Bitcoin, and (Wang et al., 2020) reach a comparable conclusion regarding their use as hedges and diversifiers within cryptocurrency portfolios. Both findings indicate that the stablecoin sector absorbs and retains risk rather than transmitting it unaltered.

This literature does not, however, trace the shock beyond the cryptocurrency sector. Peg mechanics, run dynamics and contagion between coins are all documented; transmission to equity market volatility is not.

- **Crypto and Equity Markets, and the Indian Evidence**

The transmission literature is mixed, and this heterogeneity is itself informative. (Bouri et al., 2016) apply a dynamic conditional correlation model and find that Bitcoin performs poorly as a hedge, serving principally as a diversifier, with safe-haven properties evident only against weekly extreme downward movements in Asian equities. (Corbet et al., 2018), working in the time and frequency domains, report that cryptocurrencies remain relatively isolated from conventional financial and economic assets, with diversification benefits concentrated at short horizons.

For India the evidence is more limited. (Thomas, 2024) estimates a multi-index dynamic multivariate GARCH model and identifies volatility linkages between Bitcoin and the major Indian indices that are interconnected but short-lived, with correlations responding rapidly to news. (Murty et al., 2022) examine whether Bitcoin serves as a safe haven for Indian investors within a GARCH framework. Considered collectively, the evidence describes a linkage that is weak, unstable and dependent upon the horizon of measurement. Each of these studies employs Bitcoin or an aggregate index on the cryptocurrency side; none employs a stablecoin-specific stress measure, which constitutes the gap addressed here.

- **Econometric Foundations**

(Mandelbrot, 1963) established the leptokurtic and clustered character of speculative price changes. (Engle, 1982) formalised conditional heteroskedasticity and supplied the Lagrange multiplier test employed here; (Bollerslev, 1986) generalised the model to the GARCH form estimated as the symmetric benchmark. (Nelson, 1991) developed the exponential specification adopted in this study, which models the logarithm of the conditional variance and therefore requires no non-negativity restrictions upon the coefficients, whilst permitting the sign and magnitude of a shock to enter separately. (Glosten et al., 1993) provide the threshold alternative against which it is compared. Standard errors throughout follow (Bollerslev & Wooldridge, 1992), which remain valid under misspecification of the conditional density. Stationarity is assessed using (Dickey & Fuller, 1979) and (Phillips & Perron, 1988), which specify a unit root under the null, together with (Kwiatkowski et al., 1992), which reverses the hypothesis structure and therefore furnishes confirmatory rather than merely corroborative evidence. (Carnero et al., 2006) inform the treatment of extreme observations discussed in Section 5.3.

Research Methods

- **Data**

The sample covers 31 December 2018 to 31 December 2024 and contains 1,479 National Stock Exchange trading days. Return construction reduces this to 1,478 observations, and specifications with lagged regressors use 1,477. The series are the NIFTY 50 closing level, the India VIX, the USD/INR reference rate, Bitcoin, Tether and USD Coin closing prices, the effective federal funds rate, and West Texas Intermediate spot prices. They come from the National Stock Exchange, the Reserve Bank of India Database on the Indian Economy, yahoo finance, the Federal Reserve Economic Data service and the U.S. Energy Information Administration. Returns are continuously compounded daily log differences multiplied by 100. The India VIX enters in log differences and the federal funds rate in first differences.

- **Calendar Alignment and Missing Values**

The NSE calendar serves as the master index, since conditional volatility may only be modelled on days upon which the receiving market trades. Cryptocurrency prices are sampled at NSE closes and are never averaged across non-trading days: averaging weekend prices into a Monday observation would generate a price that never traded and would suppress measured variance, a first-order error in a study whose dependent variable is variance. Information arriving whilst the exchange is closed accumulates into the return of the following session, which is the standard treatment of the weekend effect (French, 1980) and of non-synchronous trading (Lo & MacKinlay, 1989). Weekend cryptocurrency movement is not discarded, since the depeg measure aggregates across the full interval.

Missing values were addressed by carrying the last observation forward rather than by interpolation. The justification concerns identification rather than convenience. Interpolation of any form employs a future value to construct a present one, thereby introducing look-ahead bias into the information set upon which the conditional variance is conditioned, inflating the persistence parameter and distorting the asymmetry parameter that the model exists to estimate. Fourteen India VIX observations, one USD/INR observation, ten WTI observations and all United States holiday gaps in the federal funds rate were treated in this manner. The funds rate is in any case an administered step function, for which interpolation would introduce drift that does not exist. The NIFTY 50 series required no imputation whatsoever.

- **Negative WTI Prices and Extreme Observations**

WTI settled at -$36.98 on 20 April 2020 when a contract-expiry storage constraint overwhelmed the physical delivery point at Cushing. This constitutes a genuine market outcome rather than a recording error, yet the logarithmic return is undefined at a non-positive price. Deletion of the observation would remove a genuine volatility observation from the most turbulent period of the sample; taking the absolute value would assert a price that never traded; and the addition of a constant offset would alter every return in the series. The value for that date was instead reconstructed by applying the same-day Brent logarithmic return to the preceding WTI close. Brent traded continuously and positively throughout the session, shares the global demand shock, and is unaffected by the Cushing-specific delivery constraint that drove WTI below zero. The resulting value of $16.83 preserves a decline of approximately 18.9%, so that the episode remains within the volatility record whilst the logarithm remains defined.

No return series was winsorised or trimmed. In volatility modelling, extreme observations constitute the object of study rather than contamination, and (Carnero et al., 2006) demonstrate that their removal biases both the size and asymmetry parameters of GARCH models and may eliminate the leverage effect entirely. The appropriate response to leptokurtosis is a fat-tailed conditional density, which is why estimation proceeds under a Student's t.

- **Measuring Depeg Intensity**

A fixed two-sided rule flagging any absolute deviation beyond 0.5% is unsuitable for this sample. Such a rule identifies 134 Tether days and 133 USD Coin days, approximately 9% of all observations, and the distribution of those flags demonstrates why they cannot be interpreted as depegs. The majority fall in 2019; the mean absolute deviation in that year exceeds that of the March 2023 banking episode by an order of magnitude; the 2019 deviations are positive rather than negative; and Tether and USD Coin deviations correlate at +0.49 across that year. Two coins supported by independent collateral do not breach parity upward in unison, so this represents thin early-market exchange pricing rather than loss of the peg. A rule that disregarded this would load 2019 microstructure noise as the dominant shock and bias the coefficient of interest towards zero. The two-sided form is additionally inappropriate on its own terms, since a coin trading above par is not breaking the buck.

Three corrections were therefore applied. Deviation is measured on the downside only, as the positive part of unity less the price. For each NSE day the measure records the maximum downside deviation across the calendar interval since the preceding NSE close. This second step is necessary: USD Coin reached a low of $0.9715 on Saturday 11 March 2023, such that close sampling eliminates the most significant episode of the sample entirely, whereas interval aggregation records it at 2.85% intensity on Monday 13 March 2023, the first session upon which Indian investors could transact. The event threshold is then rendered era-aware, flagging deviations exceeding a rolling 250-day median plus three scaled median absolute deviations, subject to a floor of 0.25%, following robust outlier practice (Rousseeuw & Croux, 1993). This procedure yields 24 Tether and 30 USD Coin depeg days, 43 in composite, capturing March 2020, May 2022 and March 2023 whilst excluding the 2019 noise. The variable employed in estimation, DEPEG_INT, is the interval-maximum downside deviation expressed in percentage points.

One feature of the resulting series conditions the interpretation of the findings. Of the 43 depeg days, 41 fall within 2019-2020 and only two occur after 2021, on 11 May 2022 and 13 March 2023. The statistical power available to distinguish a stablecoin-specific effect from pandemic-era common shocks is therefore constrained by the events themselves rather than by the estimator.

- **Model Specification**

Three candidate mean equations were compared on the Schwarz criterion, and the specification with autoregressive terms at lags one and five was selected. Three conditional variance specifications were then estimated under a Student's t density: the symmetric GARCH (1,1), the threshold model, and the exponential model. The selected variance equation (Log-GARCH with asymmetry and exogenous variables) is:

$$\ln(\sigma^2_t) = \omega + \alpha|z_{t-1}| + \gamma z_{t-1} + \beta \ln(\sigma^2_{t-1}) + \theta' X_{t-1}$$

where z is the standardised residual, α measures the effect of shock size, γ the effect of shock sign, β the persistence of volatility, and X collects the exogenous variance regressors: lagged depeg intensity, crude oil returns and, in the second model, a dummy for the March-April 2020 disruption. The conditional mean (AR model with crypto spillover) is:

$$R\_NIFTY_t = \mu + \varphi_1 R\_NIFTY_{t-1} + \varphi_5 R\_NIFTY_{t-5} + \delta R\_BTC_{t-1} + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim t(v)$$

Cryptocurrency regressors enter with a lag by design. The NSE closes at 15:30 IST whilst cryptocurrency markets continue to trade, so a contemporaneous term would conflate genuine predictive transmission with mechanical overlap. Lagging renders the test strictly predictive, as the efficiency argument of Section 1 requires. Estimation proceeds by maximum likelihood using BFGS with Marquardt steps, with standard errors given by the QML sandwich estimates of (Bollerslev & Wooldridge, 1992).

Analysis of Data

- **Descriptive Statistics**

Table 1 reports summary statistics. NIFTY 50 returns average 0.0526% per trading day with a standard deviation of 1.1657%, consistent with the upward drift of Indian equities across the six-year window. The distribution is markedly negatively skewed at -1.5860, so that large declines occur more frequently than large advances of comparable magnitude, and kurtosis of 24.8431 substantially exceeds the Gaussian benchmark of 3. The Jarque-Bera statistic of 30,002.21 rejects normality decisively, as it does for every other series reported.

Table 1: Descriptive Statistics, 31 December 2018 to 31 December 2024

Statistic	R_NIFTY	R_BTC	R_USDINR	R_WTI	D_EFFR	D_LN_VIX	DEPEG_INT
Mean	0.0526	0.2177	0.0138	0.0320	0.0013	-0.0001	0.0476
Median	0.0952	0.1067	0.0024	0.1512	0.0000	-0.0034	0.0039
Maximum	8.4003	20.3046	2.6395	42.5832	0.7500	0.3524	2.9876
Minimum	-13.9038	-46.4730	-2.3115	-59.1288	-0.8500	-0.3531	0.0000
Std. Dev.	1.1657	4.2501	0.3748	3.9621	0.0565	0.0535	0.1746
Skewness	-1.5860	-1.0560	0.3604	-1.1574	3.8550	0.5578	11.5440
Kurtosis	24.8431	16.4326	9.7474	62.1398	138.0214	9.6095	173.6384
Jarque-Bera	30002.21	11386.48	2835.76	215718.6	1126372	2766.93	1825979
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1478	1478	1478	1478	1478	1478	1478

Note. Kurtosis is reported on the EViews convention, so the Gaussian benchmark is 3. DEPEG_INT is downside depeg intensity in percentage points.

Source: Author's computation using EViews.

Two implications follow for the modelling strategy. Negative skewness combined with pronounced leptokurtosis constitutes the canonical signature of asymmetric volatility, which favours a specification permitting negative and positive innovations to operate differently. The tails are additionally heavy enough that a conditional Gaussian density would be misspecified, supporting the Student's t. The extreme skewness and kurtosis of DEPEG_INT reflect its construction: the variable equals zero on the majority of trading days and assumes large values only during a small number of episodes.

- **Autocorrelation Structure**

The correlogram of NIFTY 50 returns over twenty lags reveals modest but statistically detectable linear dependence, with a first-order coefficient of -0.060 and a fifth-order coefficient of 0.121. The Ljung-Box statistic at lag ten is 72.716 ($p < .001$). These two spikes determine the lag structure of the conditional mean equation.

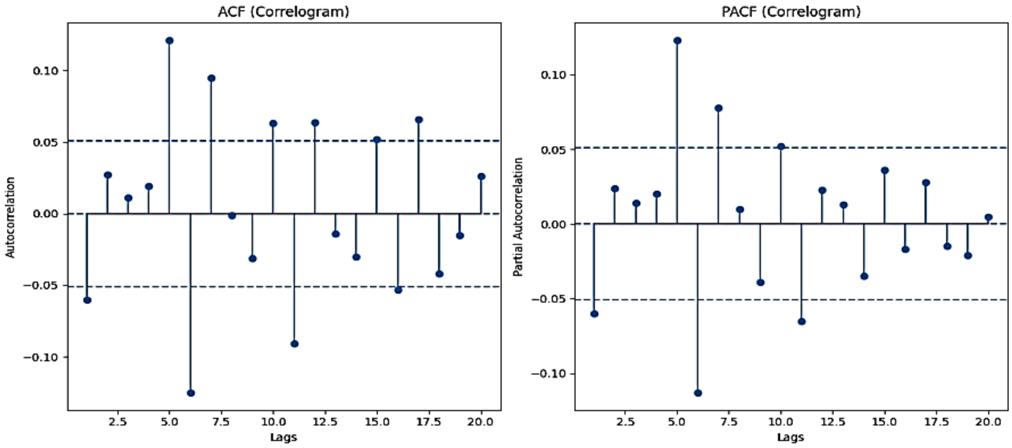

Figure 1: Autocorrelation and Partial Autocorrelation Functions (Correlogram) of Return Series

Source: Author's computation.

Squared returns present a categorically different picture. The autocorrelations are uniformly positive and substantially larger, at 0.197 at lag one, 0.332 at lag two, 0.368 at lag seven and 0.363 at lag nine, whilst the Ljung-Box statistic reaches 949.09, approximately thirteen times the corresponding figure for raw returns. The autocorrelation function decays slowly rather than truncating, and every coefficient through lag twenty remains significant. Large movements cluster irrespective of sign, which is the phenomenon that GARCH models exist to capture (Mandelbrot, 1963; Engle, 1982). Figure 2 displays this directly: absolute returns remain subdued for extended intervals before spiking sharply around March 2020, with smaller clusters in 2022 and 2024.

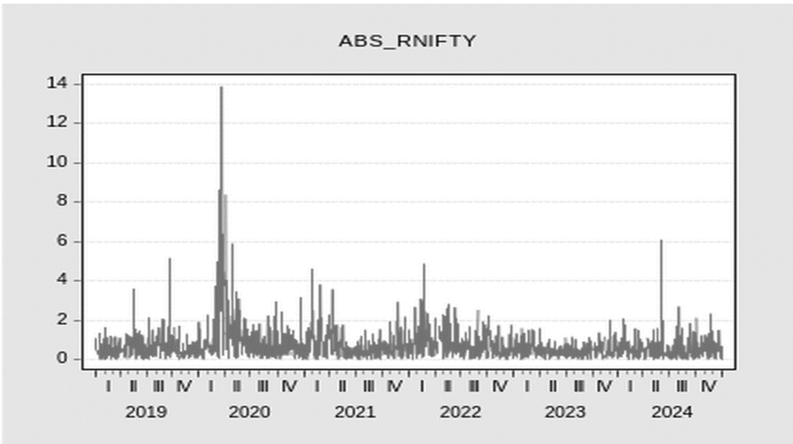

Figure 2: Absolute NIFTY 50 Daily Returns, Showing Volatility Clustering

Source: Author's computation using EViews.

Formal testing confirms the visual evidence. The Lagrange multiplier test of (Engle, 1982), applied to the residuals of the selected mean equation with ten lags, yields Obs×R^2 = 469.9454 and F (10, 1457) = 68.6045, both significant at $p < .001$. Seven of the ten lagged squared residual terms are individually significant at the 5% level, with the largest contributions at lags two, seven and nine. Ordinary least squares estimation of the conditional mean is therefore inappropriate, and GARCH-family modelling is required.

- **Stationarity**

Every member of the GARCH family requires covariance-stationary inputs, so the order of integration of each series was established prior to estimation. All specifications include an intercept; ADF lag lengths were selected automatically by the Akaike information criterion, and the PP and KPSS bandwidths by the Newey-West procedure using a Bartlett kernel. Table 2 reports the results.

Table 2: Unit Root and Stationarity Tests

Series	ADF t	p	PP adj. t	p	KPSS LM	Order
Panel A: Levels						
NIFTY	-0.3070	.9214	-0.3038	.9219	4.3118	I(1)
BTC	–0.6890	.4909	-0.0810	.9496	2.5002	I(1)
USDINR	-0.4419	.8995	-0.6344	.8604	4.3945	I(1)
WTI_SPOT	-1.7525	.4045	-1.9704	.3002	2.2727	I(1)
EFFR	-0.1089	.9466	-0.1641	.9404	3.0231	I(1)
Panel B: Returns and transformed series						
R_NIFTY	-11.3041	.0000	-40.7481	.0000	0.0473	I(0)
R_BTC	-17.7382	.0000	-39.8102	.0000	0.1415	I(0)
R_USDINR	-11.7780	.0000	-48.8316	.0001	0.0341	I(0)
R_WTI	-10.1515	.0000	-43.6011	.0001	0.0509	I(0)
D_LN_VIX	-9.2547	.0000	-38.9277	.0000	0.0258	I(0)
D_EFFR	-38.3255	.0000	-38.3958	.0000	0.7705	see note
DEPEG_INT	-6.4136	.0000	-33.6899	.0000	0.6550	see note

Note. ADF and PP critical values are approximately –3.4346, –2.8633, and –2.5678 at the 1%, 5%, and 10% levels. KPSS asymptotic critical values are 0.7390, 0.4630, and 0.3470. p-values are one-sided. D_EFFR and DEPEG_INT reject the unit root null decisively but also reject the KPSS null, for reasons explained in the text; both enter only as exogenous variance regressors. Source: Author's computation using EViews.

Panel A shows that all price and rate series in levels (NIFTY, BTC, USDINR, WTI, EFFR) are integrated of order one. The two hypothesis structures concur: ADF and PP fail to reject the unit root null, while KPSS rejects stationarity, with the NIFTY statistic nearly six times the 1% critical value. Panel B demonstrates that logarithmic differencing induces stationarity, with all three tests in agreement for R_NIFTY, R_BTC, R_USDINR, R_WTI, and D_LN_VIX, each classified as I(0). D_EFFR is a sparse step process in which non-zero changes cluster around discrete policy decisions; its KPSS statistic reflects the level shift during the 2022–23 tightening cycle. DEPEG_INT is censored at zero by construction, and a variable bounded below cannot contain a unit root by definition. Neither enters the conditional mean equation, so the covariance-stationarity requirement does not bind for either.

- **Choosing the variance specification**

Three candidate mean specifications were compared on the Schwarz criterion: AR (1) attained -2320.639 and 3.155057, MA (1) attained -2320.774 and 3.155239, and AR (1)-AR (5) attained -2309.533 and 3.144966. The last also minimises the Akaike and Hannan-Quinn criteria and was accordingly selected; its inverted autoregressive roots lie within the unit circle. Table 3 compares the three variance specifications estimated upon that mean equation.

Table 3: Comparison of Conditional Variance Specifications

Model	Log-likelihood	AIC	SIC	HQ
GARCH (1,1)-t	-1947.499	2.644789	2.669883	2.654144
GJR-GARCH (1,1)-t	-1931.991	2.625157	2.653836	2.635849
EGARCH (1,1)-t	**-1930.058**	**2.622541**	**2.651220**	**2.633233**

Note. All models use an AR (1)-AR (5) mean equation, a Student's t density and QML standard errors, with N = 1,478. The preferred specification is in bold. *Source: Author's computation using EViews.*

The exponential specification attains the highest log-likelihood and simultaneously minimises all three information criteria. Symmetry is decisively rejected: a likelihood ratio test of the threshold model against GARCH (1,1) yields 31.02 on one degree of freedom. The degrees-of-freedom parameter of the Student's t density lies between 5.77 and 6.44 across specifications and is significant at the 1% level in each case, supporting H4.

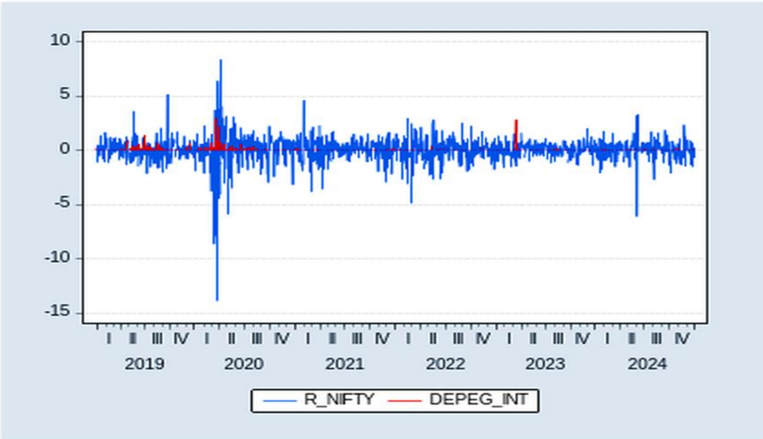

Figure 3: NIFTY 50 daily returns and stablecoin depeg intensity, 2019-2024

Source: Author's computation using EViews.

Figure 3 plots the two series jointly and anticipates the identification problem addressed in Section 7. Depeg intensity is concentrated within the earlier portion of the sample, coinciding with the period in which NIFTY volatility was at its highest for reasons unrelated to stablecoins.

Results and Discussion

Table 4 reports the principal estimates. Model 1 is the baseline exponential GARCH specification incorporating depeg intensity and crude oil returns in the variance equation. Model 2 adds a dummy variable for the March-April 2020 disruption. The two specifications differ by exactly one regressor, so the marginal contribution of that control is directly identified.

Table 4: EGARCH (1,1) Estimates of NIFTY 50 Conditional Volatility

Parameter	Model 1: Baseline		Model 2: With COVID control	
	Coefficient	z (p)	Coefficient	z (p)
Conditional mean equation				
Constant	0.0788***	3.472 (.0005)	0.0768***	3.342 (.0008)
R_BTC (-1)	0.0199***	3.863 (.0001)	0.0199***	3.902 (.0001)
AR (1)	0.0664**	2.329 (.0198)	0.0685**	2.363 (.0181)
AR (5)	-0.0049	-0.207 (.8362)	-0.0033	-0.139 (.8894)
Conditional variance equation				
ω (constant)	-0.1185***	-4.391 (.0000)	-0.1293***	-3.322 (.0009)
α (size)	0.1396***	4.510 (.0000)	0.1471***	3.609 (.0003)
γ (asymmetry)	-0.1073***	-4.626 (.0000)	-0.1243***	-4.645 (.0000)
β (persistence)	0.9635***	62.848 (.0000)	0.9422***	32.961 (.0000)
DEPEG_INT (-1)	0.0764	0.879 (.3796)	-0.0288	-0.268 (.7889)
COVID_CRASH	—	—	0.1774*	1.795 (.0726)
R_WTI	-0.0093	-1.298 (.1942)	-0.0056	-0.796 (.4258)
t degrees of freedom	6.1039***	6.288 (.0000)	6.4398***	5.757 (.0000)
Log-likelihood	-1919.244		-1915.158	
AIC	2.613736		2.609557	
SIC	2.653192		2.652599	
Observations	1477		1477	

Note. Maximum likelihood under a Student's t density, BFGS with Marquardt steps. Standard errors are QML sandwich estimates using the observed Hessian. *** p < .01, ** p < .05, * p < .10. *Source: Author's computation using EViews.*

- **Asymmetry and Persistence**

The size parameter is positive and significant at the 1% level in both specifications, and the asymmetry parameter is negative and significant at the same level (-0.1073, z = -4.626; -0.1243, z = -4.645). H1 is supported. A negative innovation to Indian equity returns raises conditional variance by more than a positive innovation of equal magnitude, consistent with the leverage argument of (Black, 1976) and the volatility feedback mechanism of (Campbell & Hentschel, 1992), and accounting for the superiority of the exponential specification in Table 3.

Persistence is high but stationary, at 0.9635 in Model 1 and 0.9422 in Model 2, in both cases strictly below unity. In the exponential specification persistence is measured by β alone rather than by $\alpha + \beta$, since the equation is expressed in logarithms and the terms are not additive as in the symmetric model. The implied half-life of a volatility shock is approximately 18.6 trading days under Model 1 and 11.6 under Model 2, so that shocks decay over roughly two to four calendar weeks.

- **The Depeg Coefficient**

The coefficient on lagged depeg intensity constitutes the central test. In the baseline specification the estimate is positive at 0.0764 but statistically insignificant (z = 0.879, p = .380), with a standard error of 0.0870 exceeding the coefficient itself. Inclusion of the pandemic dummy is decisive: the depeg coefficient reverses sign to -0.0288 with p = .789, whilst the dummy enters positively at 0.1774 with p = .073. H2 is not supported.

The likelihood ratio test of Model 2 against Model 1 yields 8.17 on one degree of freedom (p = .004), confirming that the pandemic control belongs in the specification, and the Schwarz criterion likewise favours Model 2 at 2.652599 against 2.653192. Once that control is present, depeg intensity contributes no incremental explanatory power.

The sign reversal is diagnostic, and Figure 3 accounts for it. Depeg episodes within this sample fall predominantly inside the pandemic window, so the weak positive coefficient in the baseline reflects common exposure to the March 2020 turmoil rather than an independent channel running from stablecoins to Indian equities. Once that shared exposure is absorbed by the dummy, no residual explanatory power remains. Re-estimation under a Gaussian density with outer-product-of-gradients standard errors reproduces the pattern closely, yielding 0.0808 (p = .129) in the baseline and -0.0136 (p = .844) with the control, so the result is invariant to the assumed conditional density and to the covariance estimator. Crude oil returns are insignificant in both specifications.

- **Transmission through Returns**

The null result on the variance channel must be read alongside a significant result in the conditional mean. Lagged Bitcoin returns enter positively at 0.0199 in both specifications with p < .001, and the coefficient is remarkably stable across models. A one percentage point increase in Bitcoin returns is associated with approximately a 0.02 percentage point increase in next-day NIFTY 50 returns. H3 is supported.

Considered jointly, the two findings characterise the route by which cryptocurrency markets reached Indian equities over this period. Broad movements in the cryptocurrency market predicted Indian equity returns, whereas breakdowns in stablecoin pegs did not predict Indian equity volatility. Indian participants appear to have responded to aggregate cryptocurrency performance without pricing stress in stablecoin infrastructure as a distinct risk factor. This accords with the wider evidence (Corbet et al., 2018) report relative isolation of cryptocurrencies from conventional assets, and (Thomas, 2024) identifies Indian volatility linkages with Bitcoin that are demonstrable but short-lived. A weak and horizon-dependent connection is precisely what would generate a detectable mean effect alongside an undetectable variance effect at daily frequency.

The limitations of the test warrant explicit statement. Only two clean idiosyncratic depegs occur after 2021. Around those two dates the mean absolute next-day NIFTY return was 1.45% against an unconditional value of 0.67%, approximately double and in the anticipated direction, yet two observations cannot be distinguished from noise at any conventional significance level. The appropriate characterisation is that the effect is economically suggestive but statistically unidentifiable within this sample.

- **Diagnostics**

Table 5 reports post-estimation testing. Both specifications continue to reject the null of no remaining conditional heteroskedasticity at the 5% level. The magnitude of the improvement is nonetheless substantial: against a pre-estimation statistic of 469.9454, the exponential specification absorbs approximately 95% of the conditional heteroskedasticity present in the raw residuals, and only one lag of ten attains individual significance in either model. Residual dependence confined to an isolated lag is characteristic of daily equity data, although a fully adequate specification would fail to reject, and this constitutes a limitation of the models reported. An EGARCH (1,2) specification represents a natural extension. Durbin-Watson statistics of 2.276 and 2.280 indicate no material first-order serial correlation remaining in the mean equation residuals.

Table 5: Post-Estimation ARCH-LM Diagnostics

Test	Model 1	Model 2
ARCH-LM (10), Obs×R^2	23.7257	24.5815
p (chi-square)	.0084	.0062
ARCH-LM (10), F-statistic	2.3935	2.4813
p (F)	.0081	.0060
Pre-estimation Obs×R^2	469.9454	469.9454
Reduction in test statistic	94.9%	94.8%
Durbin-Watson	2.276	2.280

Note. Tests are computed on weighted standardised squared residuals with White heteroskedasticity-consistent standard errors. *Source: Author's computation using EViews.*

Suggestions

The first recommendation concerns measurement. Researchers applying a fixed peg-deviation threshold should examine the deviation series by year prior to estimation. In this sample a rule that appears defensible on its face flagged approximately 9% of trading days and rendered 2019 exchange pricing noise the dominant shock, and this would not have been detected by any procedure that did not inspect the flags directly. Downside-only measurement, an era-aware robust threshold, and aggregation to the calendar of the receiving market should be regarded as minimum standards rather than refinements.

The second concerns statistical power. Two clean depegs after 2021 are insufficient for a daily single-market design, and this should be assessed before estimation rather than discovered subsequently. Three approaches would assist: intraday data on the receiving market around narrow event windows, a cross-country panel pooling depeg episodes across several equity markets, or a longer sample as further episodes accumulate. The panel design appears most promising, since it holds the event fixed whilst permitting the receiving market to vary.

Third, several extensions would strengthen the analysis reported here: an EGARCH (1,2) specification to accommodate the residual dependence at lag five, structural break testing so that the pandemic window is identified endogenously rather than imposed, a sensitivity check upon the reconstructed WTI observation, and out-of-sample forecast evaluation.

For practitioners and regulators, the finding is reassuring but conditional. Across these six years stablecoin peg stress did not transmit measurably into Indian equity volatility, which suggests that the market was insulated from cryptocurrency infrastructure risk at daily frequency. Such insulation should not be presumed permanent. It most probably reflects the limited institutional overlap between cryptocurrency and equity holdings in India during the sample period rather than any structural barrier, and merits re-examination as tokenised instruments and regulated cryptocurrency intermediation expand.

Conclusion

This study examined whether stablecoin depegs matter for Indian equity volatility. Employing 1,478 daily NIFTY 50 observations from 31 December 2018 to 31 December 2024 and an exponential GARCH specification with a Student's t density, the answer is that they do not, at least not in any manner these data can identify. Depeg intensity is insignificant in the baseline specification, reverses sign once pandemic-period co-movement is controlled, and behaves identically under an alternative conditional density and covariance estimator. Lagged Bitcoin returns, by contrast, predict next-day NIFTY 50 returns at the 1% level. Transmission to Indian equities therefore operated through returns rather than through stablecoin-specific volatility.

The volatility findings themselves are unambiguous. NIFTY 50 returns display pronounced negative skewness, heavy tails, decisive rejection of normality and strong volatility clustering. The exponential specification dominates both the symmetric and threshold alternatives on all three information criteria, the asymmetry parameter is negative and significant at the 1% level in both specifications, and persistence is high but stationary, with shocks decaying over two to four weeks.

Two contributions merit emphasis alongside the principal result. The first is measurement: a fixed two-sided threshold misclassifies early-market noise as depegging, and close-to-close sampling would have eliminated the March 2023 USD Coin episode from the dataset entirely. The second concerns the limits of the test itself. Only two clean idiosyncratic depegs occurred after 2021, and around those dates the next-day absolute return was approximately double its unconditional value. This is suggestive but not separable from noise. Whether stablecoin depegs matter for equities remains an open question; what this study establishes is that, within this sample, there is no statistically detectable effect on Indian equities using daily data across the observed window.

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