

A Semi-Parametric Copula Analysis of Asymmetric Dependence Between Indian and U.S. Stock-Equity Markets

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ABSTRACT

This study examines the dependence structure between Indian and U.S. equity markets using a semi-parametric copula-based framework that accounts for nonlinear and asymmetric co-movements. Daily closing price data for the NIFTY index and the NASDAQ Composite index, obtained from Yahoo Finance over the period January 2016 to March 2025, are analyzed. Marginal return distributions are modeled nonparametrically using empirical distribution functions, while the joint dependence structure is characterized through parametric copula models capable of capturing tail dependence. Copula parameters are estimated using likelihood-based methods, and model adequacy is evaluated through formal goodness-of-fit criteria. The empirical findings reveal significant asymmetric dependence between the two markets, with stronger co-movements observed during extreme market conditions than in the central regions of the return distribution. These results indicate that linear correlation measures understate cross-market dependence during periods of stress, thereby overstating potential diversification benefits and underscoring the importance of tail-sensitive dependence modeling in international equity markets.

Keywords: Copula Theory, Asymmetric Co-movement, Tail Dependency, Sklar's Theorem

2000 Mathematics Subject Classification: 62M10, 90-10.

1 Introduction

Traditional empirical analyses of international equity market integration have largely relied on linear dependence measures, particularly Pearson's correlation coefficient. While correlation offers a convenient summary of average co-movement, it is inadequate for capturing the complex dependence structures observed in financial data. Empirical evidence suggests that correlations are time-varying, increase sharply during periods of market stress, and fail to describe nonlinear, asymmetric, or state-dependent relationships between asset returns ((Longin and

Solnik, 2001); (Forbes and Rigobon, 2002); (Ang and Chen, 2002)). More critically, correlation provides little insight into joint extreme events, which are central to risk management, portfolio diversification, and systemic financial stability, especially during crisis periods.

In response to these limitations, the literature has increasingly emphasized dependence models that explicitly allow for nonlinearity, asymmetry, and tail dependence. A growing body of research documents that extreme losses across international equity markets occur jointly more frequently than predicted by linear or elliptical models, indicating the presence of strong tail dependence and contagion effects ((Longin and Solnik, 2001); (Poon, Rockinger and Tawn, 2004); (Bekaert, Ehrmann, Fratzscher and Mehl, 2014)). Recent studies further highlight that such tail dependence is highly dynamic over time and intensifies during episodes of heightened uncertainty, motivating the use of flexible and time-sensitive dependence structures (Cortese, 2019). These features became particularly pronounced during the COVID-19 pandemic, reinforcing the need for multivariate frameworks capable of capturing asymmetric dependence under both normal and stressed market conditions ((Zhang, Hu and Ji, 2020); (Ji, Zhang and Zhao, 2021)).

Copula theory provides a flexible and powerful framework to address these challenges by separating marginal distributions from the dependence structure (Sklar, 1959). This separation allows for the construction of joint distributions that capture nonlinear, asymmetric, and tail-dependent co-movements without imposing restrictive assumptions on individual return processes. As a result, copula-based models have been widely adopted in finance to study international market integration, financial contagion, and systemic risk ((Patton, 2006); (Joe, 2014); (Durante and Sempì, 2016)). In particular, copulas that exhibit explicit lower- and upper-tail dependence have proven effective in characterizing joint downside and upside risks across global equity markets ((Rodríguez, 2007); (Patton, 2012); (Reboredo, 2013)).

The empirical analysis in this study is conducted using daily closing prices of the NIFTY and NASDAQ Composite indices obtained from Yahoo Finance over the period January 2016 to March 2025. This sample spans multiple episodes of heightened global financial uncertainty, including the COVID-19 pandemic, the post-pandemic recovery phase, and recent geopolitical and monetary policy shocks, making it well suited for investigating extreme dependence dynamics. The study adopts a semi-parametric copula-based approach in which marginal return distributions are modeled nonparametrically using empirical distribution functions to mitigate the risk of parametric misspecification, consistent with established practice in the copula literature ((Genest, Ghoudi and Rivest, 1995); (Patton, 2006)).

The dependence structure is modeled using parametric copulas capable of capturing asymmetric tail behavior, with particular attention paid to differences between lower- and upper-tail dependence to assess whether extreme losses or gains are more strongly synchronized across the Indian and U.S. equity markets. Parameter estimation is carried out using likelihood-based methods, and model adequacy is evaluated through formal goodness-of-fit criteria. This framework enables a comprehensive and economically meaningful characterization of cross-market dependence that extends beyond conventional correlation analysis and contributes to the growing literature on international financial integration and tail risk transmission.

The contributions of this study are threefold:

- It provides updated empirical evidence on the dependence structure between the Indian and U.S. equity markets using a recent and economically significant sample period that includes major global stress events.
- By employing a semi-parametric copula framework with nonparametric marginal distributions, the study captures nonlinear, asymmetric, and tail-dependent co-movements that are overlooked by traditional linear dependence models.
- The analysis offers new insights into tail dependence and its implications for international diversification, systemic risk, and cross-market contagion, which are directly relevant for investors, policymakers, and financial regulators.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on international market dependence and copula-based modeling in finance. Section 3 presents the methodological framework, including return construction, marginal modeling, copula specification, and estimation procedures. Section 4 reports and discusses the empirical results, with particular emphasis on tail dependence and model comparison. Section 5 concludes the paper by summarizing the main findings, outlining their implications, and suggesting directions for future research.

2 Literature Review

The increasing integration of global financial markets has led to a growing body of research emphasizing the limitations of traditional linear dependence measures such as Pearson correlation. Such measures are inadequate for capturing the nonlinear, asymmetric, and tail-dependent co-movements observed in equity markets, particularly during periods of stress. To address these limitations, copula-based models have emerged as a flexible and powerful framework for modeling joint dependence structures while separating marginal behavior from dependence, as formalized by Sklar's theorem. Early work by (Caillault and Guégan, 2005) highlighted the empirical estimation of tail dependence using copulas, demonstrating that extreme co-movements in equity markets can differ substantially from the patterns suggested by linear correlations.

In the context of international equity markets, (Okimoto, 2014) documents asymmetric increasing trends in dependence across global markets using smooth-transition copula-GARCH models. This research reveals that both lower- and upper-tail dependence have intensified over time, particularly during periods of market turmoil, underscoring the importance of tail-sensitive measures for risk management and portfolio allocation. Similarly, (Arouri, Fouquau and Nguyen, 2017) employ time-varying SJC copulas to study directional tail dependence and volatility spillovers between developed and emerging markets. They find that downside tail dependence often strengthens during crises, reflecting the heightened systemic co-movement and the reduced diversification benefits that traditional linear models fail to capture.

Research focusing on emerging markets corroborates these findings. Studies on ASEAN equity markets and other emerging economies demonstrate that Student-t and time-varying copulas effectively capture complex dependence patterns, revealing significant co-crash and

co-boom behavior among market pairs, especially during major shocks (Innovation, 2020). Dynamic copula models combined with volatility models such as GARCH or regime-switching approaches further illustrate that dependence is often state-dependent and asymmetric, increasing during downturns while remaining moderate during normal periods (Cortese, 2019). These findings highlight the importance of modeling extreme co-movements, which have critical implications for international diversification and systemic risk assessment.

Beyond equities, empirical studies of tail dependence in financial and commodity markets consistently show that extreme co-movements exhibit asymmetry, with losses more strongly linked than gains (*Tail dependence structure and extreme risk spillover effects between the international agricultural futures and spot markets*, 2023). This asymmetric behavior has important economic and risk management implications, as linear correlation measures can underestimate joint extreme risk and overstate diversification benefits. Furthermore, methodological advances such as regular vine (R-vine) copulas demonstrate the potential to model high-dimensional dependence structures, decomposing complex interactions into interpretable pairwise tail relationships (Aroui et al., 2017).

Despite the growing literature on international market dependence and copula modeling, studies focusing specifically on the linkage between Indian and U.S. equity markets remain limited. India, as a significant emerging market, and the U.S., as a leading developed market, provide a unique context to study cross-market co-movements under both normal and stressed conditions. While prior research has largely concentrated on regional market interactions or developed market linkages, the asymmetric dependence between these two economically important markets, particularly during extreme market events, has not been fully examined.

The present study contributes to this literature in three ways. First, it provides updated empirical evidence on the dependence structure between the NIFTY and NASDAQ indices using a recent and economically relevant sample period from January 2016 to March 2025, which includes periods of both stability and heightened volatility, such as the COVID-19 pandemic. Second, by employing a semi-parametric copula-based approach with nonparametric marginal modeling, the study captures nonlinear and asymmetric dependence patterns overlooked by traditional parametric or correlation-based methods. Third, the analysis explicitly quantifies lower- and upper-tail dependence, offering insights into how extreme losses or gains propagate across these markets, with direct implications for risk management, portfolio diversification, and policy-making in an increasingly interconnected global financial system. Through this contribution, the study extends the application of semi-parametric copula models to a novel cross-market setting, bridging the gap between emerging and developed market dependence literature.

3 Methodology

This study employs a copula-based econometric framework to model the dependence structure between financial market returns in a manner that accommodates nonlinearity, asymmetry, and tail dependence. Traditional measures of dependence such as Pearson's correlation are inadequate in capturing extreme co-movements that often arise during periods of market stress (Zeevi and Mashal, 2002) and (Fernández-Avilés, Montero and Sanchis-Marco, 2020).

To overcome these limitations, the methodology adopts a semi-parametric approach in which marginal distributions are modeled nonparametrically while the joint dependence structure is specified parametrically through copula functions. This separation of marginal behavior from dependence, formalized through Sklar's theorem, allows for a flexible and theoretically coherent representation of cross-market linkages.

3.1 Returns Data Construction

Let $P_t^{(1)}$ and $P_t^{(2)}$ denote the closing prices of two financial market indices observed at time t , where $t = 1, 2, \dots, T$. Since price series are typically non-stationary and unsuitable for direct dependence modeling, the analysis is conducted using continuously compounded returns. For each market, log-returns are constructed as

$$R_t^{(i)} = \log P_t^{(i)} - \log P_{t-1}^{(i)}, \quad i = 1, 2, \quad (3.1)$$

which ensures approximate stationarity, variance stabilization, and time additivity. The resulting bivariate return vector is given by

$$\mathbf{R}_t = \left(R_t^{(1)}, R_t^{(2)} \right)^\top, \quad (3.2)$$

which forms the basis for all subsequent dependence modeling. Preliminary graphical analysis and descriptive statistics are used to inspect the data for stylized facts such as volatility clustering, heavy tails, and asymmetric co-movements, although these diagnostics remain exploratory in nature and do not impose distributional assumptions.

3.2 The Sklar's Theorem

The theoretical foundation of the methodology is provided by Sklar's theorem (Sklar, 1973), which states that for any bivariate joint distribution function $F_{R^{(1)}, R^{(2)}}$ with continuous marginal distributions F_1 and F_2 , there exists a unique copula function C such that

$$F_{R^{(1)}, R^{(2)}}(x, y) = C(F_1(x), F_2(y)). \quad (3.3)$$

Conversely, given any copula function $C : [0, 1]^2 \rightarrow [0, 1]$ and marginal distribution functions F_1 and F_2 , the function defined by the above relationship constitutes a valid joint distribution. This decomposition implies that the copula completely characterizes the dependence structure between the variables independently of their marginal distributions. As a result, modeling can proceed by first transforming the marginal distributions to uniform random variables on the unit interval and subsequently specifying a copula function to describe their dependence.

3.3 Marginal Modeling and Probability Integral Transform

Given the well-documented non-normality of financial returns, the marginal distributions are modeled nonparametrically to avoid potential misspecification (Kramer, 2001). For each return series $R_t^{(i)}$, the empirical cumulative distribution function is defined as

$$\hat{F}_i(r) = \frac{1}{T+1} \sum_{t=1}^T \mathbb{I} \left(R_t^{(i)} \leq r \right), \quad (3.4)$$

where $\mathbb{I}(\cdot)$ denotes the indicator function and the scaling factor $T + 1$ ensures that transformed observations lie strictly within the open unit interval. Applying the probability integral transform, each return observation is mapped to a pseudo-observation

$$U_t^{(i)} = \hat{F}_i \left(R_t^{(i)} \right), \quad i = 1, 2. \quad (3.5)$$

The transformed data $\left\{ (U_t^{(1)}, U_t^{(2)}) \right\}_{t=1}^T$ are approximately distributed as independent realizations from a joint distribution with standard uniform marginals. Any remaining structure in the transformed sample therefore reflects pure dependence between the markets, isolated from marginal effects.

3.4 Empirical Copula

To provide a nonparametric benchmark for the dependence structure, the empirical copula is constructed from pseudo-observations obtained from the marginal distributions. The empirical copula function is defined as

$$\hat{C}_T(u, v) = \frac{1}{T} \sum_{t=1}^T \mathbb{I} \left(U_t^{(1)} \leq u, U_t^{(2)} \leq v \right), \quad (3.6)$$

where $\mathbb{I}(\cdot)$ denotes the indicator function and T is the sample size. The empirical copula represents the joint empirical distribution of the transformed data and provides a consistent estimator of the true underlying copula as $T \rightarrow \infty$. While this nonparametric approach offers flexibility and serves as a useful diagnostic tool, it lacks parsimony and does not yield direct parametric measures of dependence, particularly with respect to tail behavior. Consequently, parametric copula models are employed in the subsequent analysis to facilitate inference on asymmetric and tail dependence.

3.5 Parametric Copula Models

To capture asymmetric dependence patterns commonly observed in financial markets, the analysis considers two Archimedean copula families: the Clayton copula (Clayton, 1978) and the Gumbel copula (Gumbel, 1960). These copulas are particularly suitable for modeling lower-tail and upper-tail dependence, respectively. The Clayton copula is defined as

$$C_{\text{Clayton}}(u, v; \theta) = \left(u^{-\theta} + v^{-\theta} - 1 \right)^{-1/\theta}, \quad \theta > 0. \quad (3.7)$$

This copula exhibits positive lower-tail dependence and zero upper-tail dependence, making it appropriate for capturing joint extreme losses. The corresponding lower-tail dependence coefficient is given by

$$\lambda_L = \lim_{q \rightarrow 0^+} \mathbb{P} \left(U^{(2)} \leq q \mid U^{(1)} \leq q \right) = 2^{-1/\theta}. \quad (3.8)$$

The Gumbel copula, in contrast, captures upper-tail dependence and is defined as

$$C_{\text{Gumbel}}(u, v; \theta) = \exp \left\{ - \left[(-\ln u)^\theta + (-\ln v)^\theta \right]^{1/\theta} \right\}, \quad \theta \geq 1. \quad (3.9)$$

This copula exhibits zero lower-tail dependence and positive upper-tail dependence, with the upper-tail dependence coefficient given by

$$\lambda_U = \lim_{q \rightarrow 1^-} \mathbb{P} \left(U^{(2)} > q \mid U^{(1)} > q \right) = 2 - 2^{1/\theta}. \quad (3.10)$$

The asymmetric nature of these copulas enables a clear distinction between downside and upside dependence, which is crucial for understanding financial contagion and diversification properties.

3.6 Estimation and Goodness-of-Fit

Parameter estimation is carried out using the inference functions for margins (IFM) approach (Kim, Silvapulle and Silvapulle, 2007). Under this framework, marginal distributions are estimated in the first step, after which copula parameters are estimated conditionally using the transformed pseudo-observations. Let $c(u, v; \theta)$ denote the copula density associated with a given copula function $C(u, v; \theta)$, defined as

$$c(u, v; \theta) = \frac{\partial^2 C(u, v; \theta)}{\partial u \partial v}. \quad (3.11)$$

The copula parameter vector θ is estimated by maximizing the log-likelihood function

$$\ell(\theta) = \sum_{t=1}^T \log c \left(U_t^{(1)}, U_t^{(2)}; \theta \right). \quad (3.12)$$

To evaluate the adequacy of the fitted copula models, goodness-of-fit is assessed using a Cramér–von Mises statistic based on the distance between the empirical copula and the fitted parametric copula, defined as

$$\text{CvM} = \frac{1}{T} \sum_{t=1}^T \left[\hat{C}_T \left(U_t^{(1)}, U_t^{(2)} \right) - C \left(U_t^{(1)}, U_t^{(2)}; \hat{\theta} \right) \right]^2. \quad (3.13)$$

Smaller values of this statistic indicate a closer match between the empirical dependence structure and the parametric copula model, thereby providing an objective criterion for model comparison and selection.

4 Empirical Results and Discussion

This section presents and discusses the empirical findings on the dependence structure between the Indian and U.S. equity markets, represented by the NIFTY and NASDAQ indices, respectively. The analysis proceeds from a preliminary graphical inspection of prices and returns to formal copula-based dependence modeling, with particular emphasis on tail behavior and model adequacy.

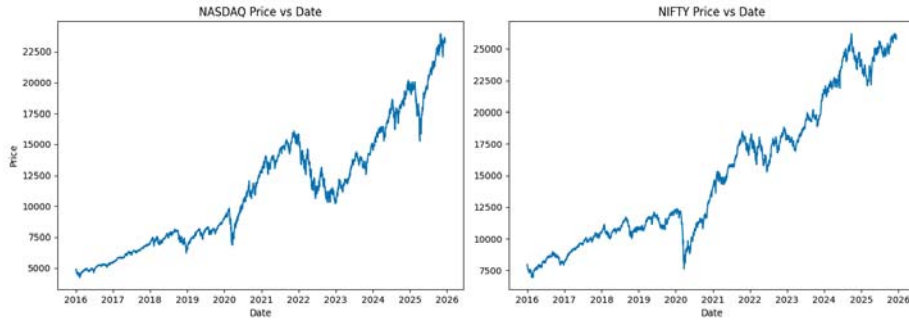


Figure 1: Daily closing prices of the NIFTY and NASDAQ indices from January 2016 to March 2025.

Figure 1 displays the daily closing prices of the NIFTY and NASDAQ indices over the sample period from January 2016 to March 2025. Both series exhibit pronounced upward trends interspersed with episodes of sharp declines, reflecting common global shocks and market-wide corrections. The non-stationary nature of the price series underscores the necessity of transforming prices into returns prior to dependence modeling. Despite differences in market size and structure, broad co-movement in long-run price dynamics is visually evident.

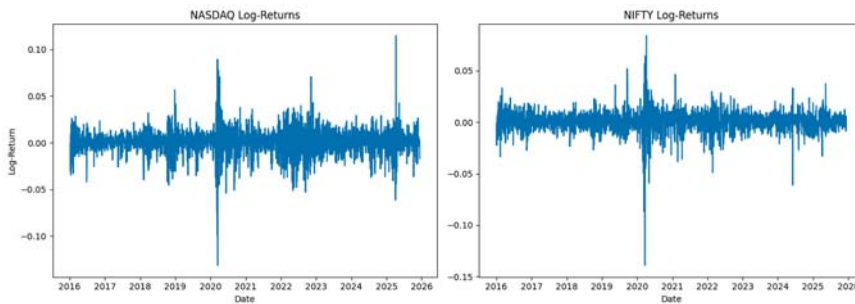


Figure 2: Daily log-returns of the NIFTY and NASDAQ indices.

Figure 2 presents the corresponding log-return series for both indices. In contrast to prices, the return series fluctuate around a zero mean and display volatility clustering, with periods of elevated variance followed by relatively tranquil intervals. Several episodes of extreme returns are observable, particularly during periods of global financial stress.

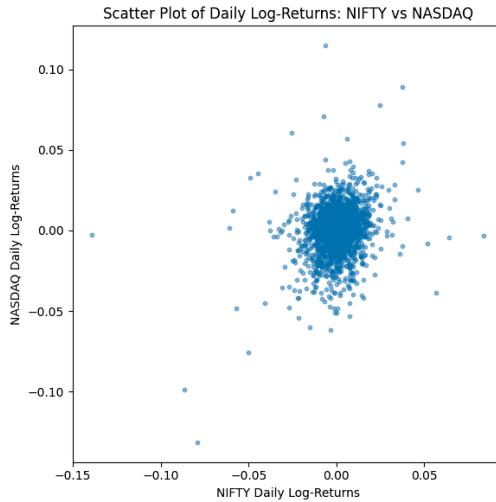


Figure 3: Scatter plot of daily log-returns of the NIFTY and NASDAQ indices.

The scatter plot of daily log-returns of the NIFTY and NASDAQ, Figure 3 indices reveals a dependence structure that is clearly non-elliptical and asymmetric, thereby motivating the use of a copula-based framework rather than a bivariate normal model. While the central mass of observations is moderately clustered around zero, the joint behavior during extreme market movements shows stronger co-movement than would be implied by linear correlation alone, with visible clustering in both large negative and large positive returns. Such tail-oriented dependence is inconsistent with the bivariate normal distribution, which enforces symmetric dependence and zero tail dependence and is therefore unable to capture contagion effects during periods of market stress or exuberance. The pronounced association in the lower tail, corresponding to simultaneous negative returns, supports the use of the Clayton copula, which is specifically designed to model lower-tail dependence and downside risk transmission across markets. At the same time, the presence of joint extreme positive returns justifies the consideration of the Gumbel copula, which captures upper-tail dependence and co-movement during bullish phases.

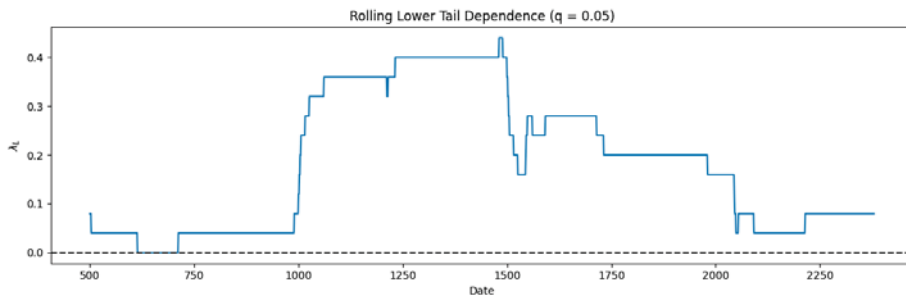
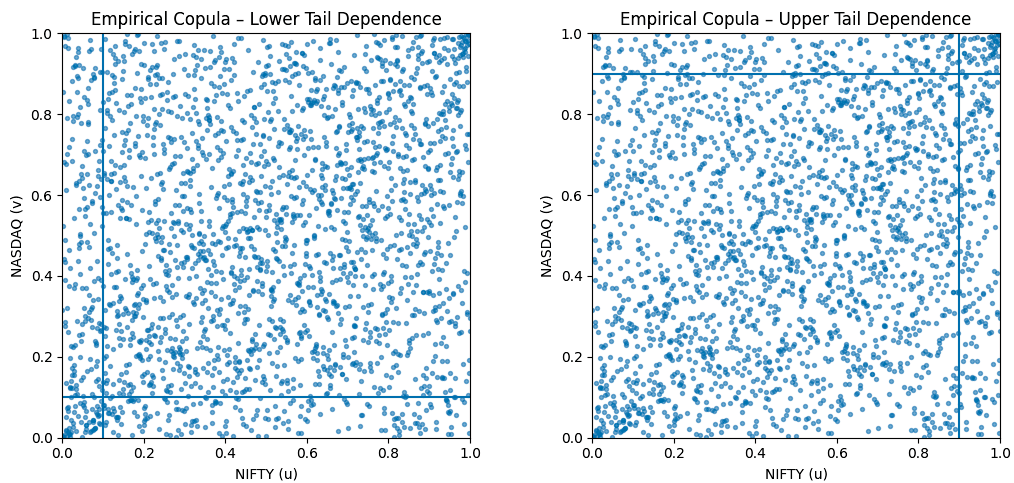


Figure 4: Rolling lower-tail dependence between NIFTY and NASDAQ returns computed using a 500-day moving window at the 5% quantile level.

Figure 4 provides complementary insights into both the static and dynamic features of dependence between NIFTY and NASDAQ returns. The scatter plot of daily log-returns illustrates a clear positive contemporaneous association, but with a visibly nonlinear and asymmetric dependence structure, as observations in the joint lower-left quadrant are more tightly clustered than those in the upper-right quadrant, indicating that large negative returns tend to occur jointly more frequently than large positive returns. This asymmetric downside co-movement is further reinforced by the rolling lower-tail dependence coefficient computed using a moving window of 500 observations at the 5% quantile level, which exhibits substantial time variation with pronounced spikes during periods of heightened global uncertainty. Together, these results suggest that extreme co-movements are neither linear nor constant over time, but instead intensify during stress episodes, implying that diversification benefits deteriorate precisely when they are most needed. The observed time-varying and asymmetric tail dependence highlights the limitations of static correlation measures and underscores the relevance of copula-based approaches for capturing systemic risk and cross-market contagion.

To further explore extremal dependence, pseudo-observations obtained via the probability integral transform are examined through empirical copula plots. Concentration of mass in the lower-left corner of the unit square confirms the existence of joint extreme losses, while upper-tail concentration appears comparatively weaker. Nonparametric estimates of tail dependence reinforce this observation: the empirical lower-tail dependence coefficient is estimated as $\hat{\lambda}_L = 0.168$, whereas the empirical upper-tail dependence coefficient is $\hat{\lambda}_U = 0.210$. Although both tails exhibit non-negligible dependence, the asymmetry in the empirical copula suggests that downside risk transmission is a particularly salient feature of the NIFTY–NASDAQ relationship.



(a) Lower-tail dependence using Empirical Copula

(b) Upper-tail dependence using Empirical Copula

Figure 5: Empirical copula estimates of lower- and upper-tail dependence between NIFTY and NASDAQ returns.

To formally quantify asymmetric dependence, Clayton and Gumbel copulas are fitted to the pseudo-observations using likelihood-based estimation. The estimated copula parameters are reported in Table 1. The Clayton copula parameter is estimated as $\hat{\theta}_C = 0.2640$, while the Gumbel copula parameter is estimated as $\hat{\theta}_G = 1.1320$. Both estimates indicate positive dependence, with each copula emphasizing different regions of the joint distribution.

Table 1: Estimated Copula Parameters

Copula	Parameter Estimate
Clayton	$\hat{\theta}_C = 0.2640$
Gumbel	$\hat{\theta}_G = 1.1320$

Using these parameter estimates, the implied theoretical tail dependence coefficients are computed. For the Clayton copula, which captures lower-tail dependence, the estimated lower-tail dependence coefficient is $\lambda_L^C = 0.0724$, while upper-tail dependence is identically zero by construction. In contrast, the Gumbel copula exhibits upper-tail dependence only, with an estimated upper-tail dependence coefficient of $\lambda_U^G = 0.1553$ and zero lower-tail dependence. These results are summarized in Table 2.

Table 2: Implied Tail Dependence Coefficients

Copula	Lower Tail (λ_L)	Upper Tail (λ_U)
Clayton	0.0724	0.0000
Gumbel	0.0000	0.1553

The presence of nonzero lower-tail dependence in the Clayton copula confirms that extreme negative returns in the Indian and U.S. equity markets tend to occur jointly more often than would be implied by linear dependence alone. At the same time, the magnitude of upper-tail dependence captured by the Gumbel copula suggests that joint extreme gains are also present, though they are relatively weaker and less persistent than joint losses. This asymmetry is economically intuitive, as global markets often react more synchronously to adverse information than to favorable news.

The adequacy of the fitted copula models is evaluated using the Cramér–von Mises (CvM) statistic, which measures the squared distance between the empirical copula and the fitted parametric copula across the sample. Smaller values of the CvM statistic indicate a closer match between the model-implied dependence structure and the observed data. The computed CvM statistics are reported in Table 3.

Table 3: Cramér–von Mises Goodness-of-Fit Statistics

Copula	CvM Statistic
Clayton	0.000025
Gumbel	0.000030

The Clayton copula yields a marginally smaller CvM statistic than the Gumbel copula, indicating a slightly superior fit to the empirical dependence structure. This result suggests that lower-tail dependence plays a more dominant role than upper-tail dependence in characterizing the joint behavior of NIFTY and NASDAQ returns. From a risk management perspective, this finding implies that downside contagion between the Indian and U.S. equity markets is a more prominent feature than synchronized extreme gains. Overall, the empirical results provide strong evidence of nonlinear and asymmetric dependence between the two markets. While both downside and upside co-movements are present, dependence is particularly pronounced in the lower tail and exhibits meaningful time variation.

5 Conclusion and Policy Implications

This study examines the dependence between the Indian and U.S. equity markets using a semi-parametric copula framework that captures nonlinear, asymmetric, and time-varying co-movements. Using daily NIFTY and NASDAQ data from January 2016 to March 2025, the analysis shows that market dependence extends well beyond linear correlation and is dominated by asymmetric tail behavior. Empirical copula estimates reveal significant lower-tail dependence, indicating that extreme negative returns tend to occur jointly more frequently than extreme positive returns, with the Clayton copula providing the best overall fit. Rolling tail-dependence estimates further demonstrate that extremal co-movement intensifies during periods of global stress, implying that diversification benefits are state-dependent and deteriorate precisely when risk is highest. Overall, the findings highlight the limitations of static correlation measures and underscore the importance of copula-based approaches for accurately assessing joint extreme risk and international market contagion.

The presence of strong and time-varying lower-tail dependence has important implications for financial stability and portfolio management. Policymakers and regulators should recognize that adverse shocks in the U.S. market can be rapidly transmitted to Indian equities during stress episodes, amplifying systemic risk, and should therefore incorporate tail-dependent measures and copula-based stress testing into macroprudential frameworks. For investors, the results indicate that traditional diversification strategies based on average correlations may underestimate downside risk, suggesting that portfolio allocation and risk management should explicitly account for asymmetric and stress-period dependence using tail-sensitive risk measures.

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