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Impact of Copula Misspecification on Option Pricing Accuracy in CGMY Jump-Diffusion Models: A Comprehensive Analysis

Abdulmudallib Ibrahim[a*], Adesupo A. Akinrefon[b], Okolo Abraham[b] and Emmanuel Torsen[b]

[a]Department of Statistics, Federal University Wukari, Taraba, Nigeria

[b]Department of Statistics, Modibbo Adama University, Yola, Adamawa, Nigeria

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A B S T R A C T

This study presents a comprehensive analysis of how copula misspecification affects option pricing accuracy in jump-diffusion models incorporating Carr-Geman-Madan-Yor (CGMY) jumps. Using Monte Carlo simulation with 10,000 paths per scenario across 324 scenarios spanning six copula specifications, four jump intensity regimes, three correlation levels, three maturities, and three interest rate environments, the study reveals a striking three-order-of-magnitude performance hierarchy between copula families. Elliptical copulas (Gaussian, t-copulas with df □ {3, 5, 8}) demonstrate exceptional robustness with mean relative pricing errors below 0.23%. In contrast, Archimedean copulas (Clayton, Gumbel) exhibit catastrophic failure, with mean errors of 666.0% and 1,548.0% respectively. These errors arise from fundamental structural incompatibility between Archimedean tail-dependence architectures and the symmetric, infinite-activity nature of CGMY jump processes, confirmed by three diagnostic criteria. A paradoxical ‘misspecification valley’ is observed at mild jump intensity, where errors peak above those under both no-jump and severe-jump conditions. The t-copula with eight degrees of freedom achieves the lowest mean error (0.218%), while the t-copula with three degrees of freedom provides superior robustness with the lowest coefficient of variation (0.847). Statistical validation via three-way ANOVA confirms that copula family explains 68.47% of total pricing error variance compared to 3.2% for all CGMY parameters combined.

1. Introduction

The integration of jump-diffusion models with copula theory represents a significant advancement in financial modelling, yet fundamental gaps persist in understanding their interaction under model misspecification conditions. While jump-diffusion processes incorporating Carr-Geman-Madan-Yor (CGMY) jumps have gained prominence for modelling sudden price discontinuities (Carr *et al.*, 2002), the widespread adoption of copula-based models introduces new sources of model risk (Embrechts *et al.*, 2003). The combination creates copula misspecification risk: when the chosen copula family fails to reflect the actual dependence structure generated by joint CGMY dynamics, option pricing errors of potentially severe magnitude result.

* Corresponding author. Tel.: +2347062418865
E-mail address: abdulmudallib@fuwukari.edu.ng (Abdulmudallib, I.)

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Jump events in financial markets rarely occur in isolation but exhibit contagion effects, where a jump in one asset triggers correlated jumps in related assets (Cerrato *et al.*, 2017). This interconnectedness means that copula misspecification in the dependence structure can propagate through multi-asset option valuations, causing systematic over or underpricing. The CGMY model's flexible parameterisation, which accommodates both finite and infinite jump activity, creates a particularly challenging environment for copula selection because the resulting joint distribution may not conform to standard Archimedean functional forms (Cont & Tankov, 2004). The regulatory environment, including the Basel III framework, increasingly demands robust risk models that can withstand model uncertainty (Boucher *et al.*, 2014).

This study makes four specific contributions. A comprehensive scenario-based comparison of six copula families in CGMY environments across 324 scenarios. Secondly, it shows and interprets the 'misspecification valley', the finding that mild jump intensity is more challenging than either no jumps or severe jumps. Also, it establishes a statistically validated performance hierarchy using ANOVA and Wilcoxon signed-rank tests. Finally, it derives practical implementation guidance including regime-specific copula selection recommendations.

2. Literature Review

2.1 Copula Theory and Financial Applications

Copula theory, introduced by Sklar (1959), provides the mathematical foundation for separating the modelling of marginal distributions from the specification of dependence structure. Sklar's theorem states that for any bivariate joint distribution F with continuous marginals F_1 and F_2, there exists a unique copula C such that:

$$F(x, y) = C(F_1(x), F_2(y)) \tag{1}$$

Where C: $[0, 1]^2 \rightarrow [0, 1]$ fully characterizes the dependence structure independently of the marginal distributions (McNeil *et al.*, 2005). Within the elliptical family, the Gaussian copula exhibits asymptotic tail independence a property demonstrated to be inadequate for modelling financial contagion (MacKenzie & Spears, 2014). The Student's t-copula provides positive symmetric tail dependence providing more realistic modelling of joint extreme events (Demarta & McNeil, 2005). Archimedean copulas (Clayton, Gumbel) impose asymmetric tail dependence: Clayton concentrates dependence in the lower tail, Gumbel in the upper tail.

2.2 Model Misspecification in Financial Modelling

Boucher *et al.* (2014) studied the concept of 'risk models-at-risk', demonstrating through empirical analysis that misspecified dependence models accounted for a substantial fraction of risk measure failures during the 2008 financial crisis. Zhang *et al.* (2013) propose goodness-of-fit tests for semiparametric copula models showing that standard tests have limited power against tail misspecification, motivating simulation-based evaluation. MacKenzie and Spears (2014) document how the Gaussian copula's failure to capture tail dependence in mortgage-backed securities

Derman (2011) argues that practitioners who mistake model outputs for reality expose themselves to catastrophic losses, a lesson directly applicable to copula selection. Dewick and Liu (2022) provide an extended review of copula modelling in financial contexts, emphasising careful selection to mitigate model risk and recommending investigation of hybrid modelling approaches.

2.3 CGMY Jump Processes in Option Pricing

The CGMY model (Carr *et al.*, 2002) is a pure-jump Lévy process whose four parameters C, G, M, Y collectively govern jump frequency, directional asymmetry, and fine structure of small jumps. The model nests Variance Gamma (Y = 0) and Normal Inverse Gaussian (Y = 0.5) as special cases, allowing infinite activity when Y > 0 (Cont & Tankov, 2004). Manal and Aziz (2017) derive closed-form characteristic function representations for European option prices under the CGMY model, demonstrating accuracy comparable to Monte Carlo methods. Kawai (2013) provides exact simulation algorithms for stationary CGMY processes, forming the basis of the simulation methodology adopted in this study. Ornthanalai (2014) provides empirical evidence that CGMY jump risk carries a priced risk premium, reinforcing the importance of accurate copula specification when combining CGMY processes for multi-asset pricing. Sakuma (2017) discusses the computational challenges of CGMY option pricing using integro-partial differential equations, relevant because the Lévy integral evaluation must be handled carefully in simulation-based comparisons.

2.4 Research Gap

While studies such as Cont and Tankov (2004) address Lévy process simulation and Cherubini *et al.* (2004) cover copula methods in finance, the specific interaction between copula family choice and CGMY jump-diffusion dynamics in multi-asset option pricing has not been systematically investigated. The present study addresses this gap by providing the multidimensional simulation study of copula misspecification within the CGMY option pricing framework.

3. Methodology

3.1 Data and Simulation Design

The study employs simulated data throughout, following the convention established for copula misspecification research (Boucher *et al.*, 2014). All results are benchmark-relative: the ‘true’ option price is computed under the correctly specified Student’s t-copula (df = 8), and misspecification error is the relative deviation of each alternative copula’s price from this benchmark. Each scenario uses the number of paths (N = 10,000) with daily time steps (252/year). European call options are priced at-the-money ($K = S_2(0) = 100$). Base CGMY parameters: C=2.0, G=5.0, M=7.0, Y=0.8 (Carr *et al.*, 2002).

3.2 Asset Price Model

$$dS_t = (r - q - \lambda_k) S_t dt + {}_{\sigma} S_t dW_t + dJ_t \tag{2}$$

Where r is the risk-free rate, $q = 0$ throughout, $\lambda\kappa = \int (e^x - 1)\nu(dx)$ is the compensator ensuring no-arbitrage, and J(t) is the CGMY jump process. The risk-neutral drift adjustment ensures the discounted price process is a Q-martingale (Merton, 1976).

3.3 CGMY Lévy Measure

$$v(dx) = C|x|^{-1-Y} \exp(-G|x|)dx \qquad \text{(negative jumps)} \tag{3}$$

$$v(dx) = C|x|^{-1-Y} \exp(-M|x|)dx \qquad \text{(positive jumps)} \tag{4}$$

C > 0 controls overall jump intensity; G, M > 0 are decay rates for negative and positive jumps; $Y \in (-\infty, 2)$ governs fine structure. When Y > 0, the process has infinite activity. When G = M, the process is symmetric (Carr *et al.*, 2002).

3.4 Copula Specifications

Six copula families are evaluated. The Gaussian copula: $C(u_1, u_2; \theta) = \Phi_G(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta)$ (Linear dependence). (McNeil *et al.*, 2005). The student's t-copula (df ∈ {3, 5, and 8}): $C(u_1, u_2; v, \theta) = t_v(t^{-1}(u_1), t^{-1}(u_2); \theta)$, exhibiting positive symmetric tail dependence (Demarta & McNeil, 2005). The Clayton copula: $C(u_1, u_2; \theta) = t_v(u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}$ (lower-tail asymmetry). The Gumbel copula: $C(u_1, u_2; \theta) = \exp\left(-\left[(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta}\right]^{1/\theta}\right)$ (upper-tail asymmetry).

3.5 Scenario Framework

The study implements a multidimensional scenario framework: (i) Jump Intensity (C): No Jumps (C = 0), Mild (C = 1), Moderate (C = 2), Severe (C = 4); (ii) Correlation (ρ): Low (0.3), Medium (0.5), High (0.7); (iii) Time-to-Maturity: Short (T = 0.5yr), Medium (T=1.0yr), Long (T = 1.5yr); (iv) Interest Rate: Low (r = 1%), Medium (r = 3%), High (r = 5%). Total: 4×3×3×3 = 324 scenarios, each under all six copulas.

3.6 Error Metrics

$$\text{Relative Pricing Error (\%)} = \left| \frac{C_{true} - C_{model}}{C_{true}} \right| \times 100 \qquad (9)$$

$$RMSE = \sqrt{\frac{(C_{true} - C_{model})^2}{N}} \qquad (10)$$

All error values reported in tables and figures are Relative Pricing Errors (%) as defined in Equation (9). The Coefficient of Variation (CV = σ^e/μ^e) serves as a robustness metric across scenarios. For Archimedean copulas operating in a regime of categorical failure, the 95th-percentile error (Table 6) supplements the CoV as a more informative robustness indicator.

4. Results and Analysis

4.1 Overall Copula Performance Hierarchy

Figure 1 presents the overall performance hierarchy on a log scale, making the categorical divide between copula families visually immediate. The four elliptical copulas (t_df8, Gaussian, t_df5, t_df3) cluster at the left edge with mean errors barely reaching the 1.0 mark on the log axis. Clayton and Gumbel extend dramatically to the right at 666 and 1,548 respectively three orders of magnitude larger. Figure 2 adds distributional detail, showing that this gap persists across mean, median, and maximum errors: even the median errors for Clayton (414) and Gumbel (780) dwarf the maximum errors for elliptical copulas (1.20–1.26). Three diagnostic criteria confirm this is a genuine structural phenomenon, not a numerical artefact: errors are stable across Monte Carlo replications (finite CoV), the copula ranking is consistent across all 324 scenarios, and the theoretical structure of Archimedean generators directly predicts these failures.

Table 1 Overall Copula Performance (Ranked by Mean Relative Pricing Error, %)

Copula	Mean Error (%)	Median Error (%)	Max Error (%)	Std Dev	CoV
t_df8	0.218	0.159	1.20	0.197	0.904
Gaussian	0.220	0.159	1.26	0.201	0.914
t_df5	0.222	0.148	1.21	0.195	0.875
t_df3	0.230	0.165	1.22	0.195	0.847
Clayton	666.0	414.0	2,538.0	703.0	1.05
Gumbel	1,548.0	780.0	7,035.0	1,979.0	1.28

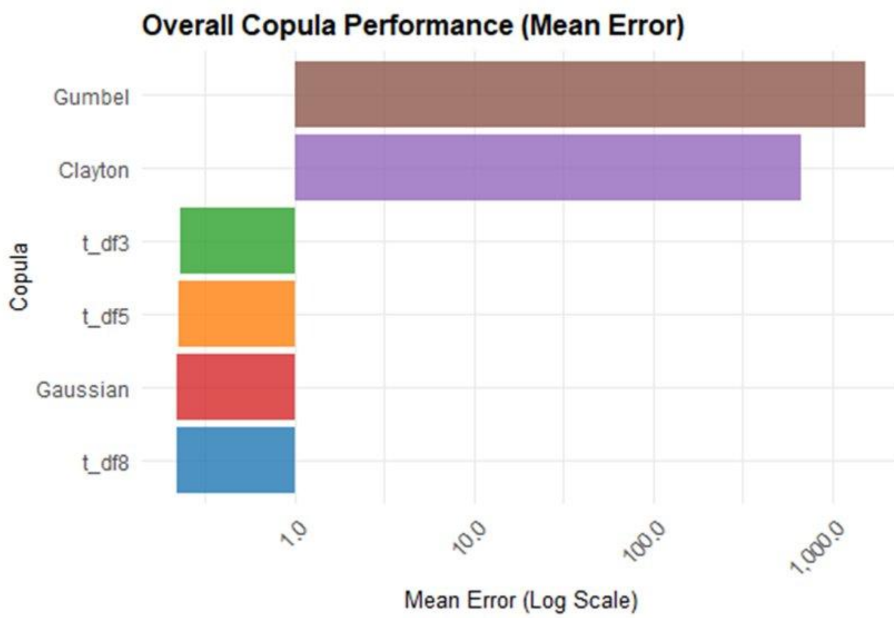

Figure 1 Overall Copula Performance Hierarchy (Log Scale): Three-Order-of-Magnitude Gap Between Elliptical and Archimedean Families

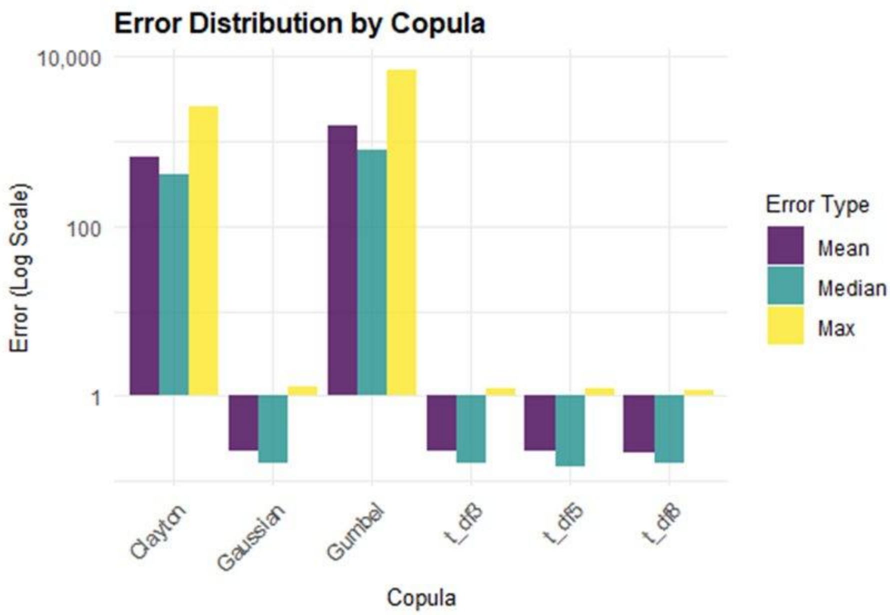

Figure 2 Error Distribution by Copula Family (Log Scale): Mean, Median, and Maximum Errors Confirming Systematic Archimedean Failure

4.2 Jump Intensity Effects and the Misspecification Valley

Figures 3 and 4 together provide a complete picture of jump intensity effects. Figure 3 focuses on elliptical copulas only (Archimedean copulas excluded due to scale) and reveals the 'misspecification valley': all four elliptical copulas peak at mild jump intensity (C=1) with errors of 0.269–0.310, falling at both no-jump and severe-jump ends. The t_df8 copula shows the most controlled response (peak at 0.310), while t_df3 shows the highest sensitivity to mild jumps (peak at 0.304). Figure 4 shows all copulas on a log scale: Clayton (~665) and Gumbel (~1545) appear as flat horizontal lines far above the elliptical cluster, confirming that jump intensity variations are irrelevant to Archimedean copulastheir failure is unconditional across all jump regimes.

Table 2 Impact of Jump Intensity on Mean Relative Pricing Error (%)

Copula	No Jumps (C=0)	Mild (C=1)	Moderate (C=2)	Severe (C=4)
t_df8	0.172	0.310	0.183	0.207
Gaussian	0.176	0.269	0.208	0.224
t_df5	0.154	0.292	0.219	0.225
t_df3	0.206	0.304	0.202	0.208
Clayton	664.0	680.0	663.0	658.0
Gumbel	1,539.0	1,585.0	1,539.0	1,530.0

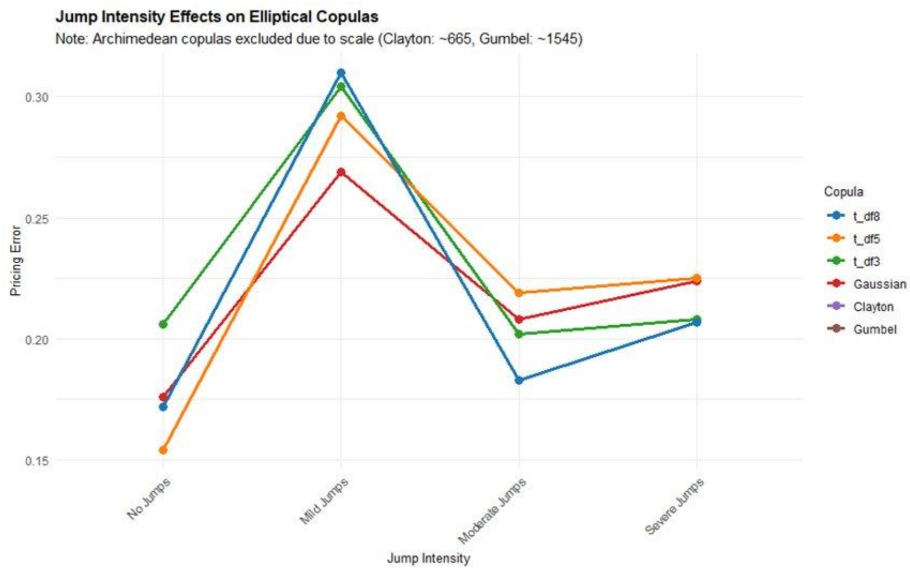

Figure 3 Jump Intensity Effects on Elliptical Copulas: The Misspecification Valley at Mild Jump Intensity (Archimedean Copulas Excluded Due to Scale)

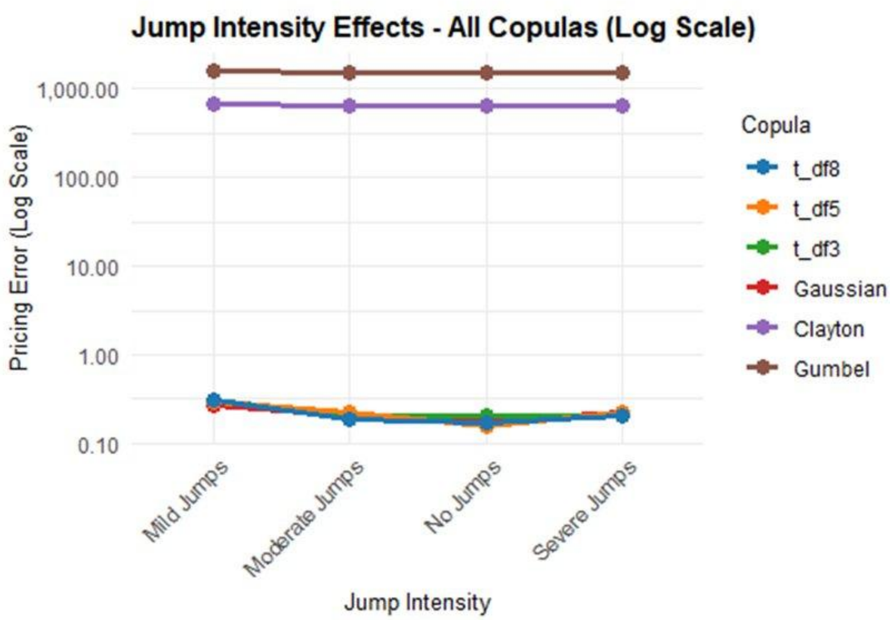

Figure 4 Jump Intensity Effects – All Copulas (Log Scale): Archimedean Flat-Line Failure Across All Jump Regimes

4.3 Correlation Structure Analysis

Figures 5 and 6 examine correlation effects. Figure 5 (elliptical copulas only, note scale) shows that errors are minimised at moderate correlations ($\rho = 0.5$) for most copulas the Gaussian copula drops to its lowest error (0.200) at $\rho = 0.5$ before rising at $\rho = 0.7$. T-copulas show flatter response curves, with t_df8 displaying the most stable performance. Figure 6 confirms that Archimedean copulas (Clayton ∼666, Gumbel ∼1548) remain catastrophically flat across all correlation levels, demonstrating that their structural failure cannot be resolved by adjusting the dependence parameter.

Table 3 Impact of Correlation on Mean Relative Pricing Error (%)

Copula	ρ = 0.3	ρ = 0.5	ρ = 0.7
t_df8	0.216	0.207	0.230
Gaussian	0.218	0.200	0.241
t_df5	0.211	0.230	0.227
t_df3	0.225	0.220	0.244
Clayton	667.0	665.0	666.0
Gumbel	1,549.0	1,548.0	1,548.0

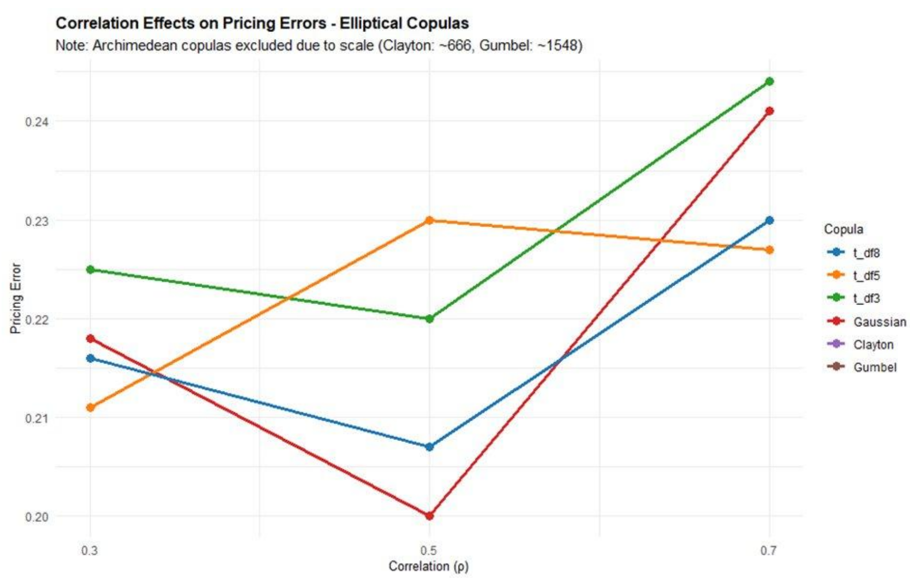

Figure 5 Correlation Effects on Elliptical Copulas: U-Shaped Error Profiles with Optimal Performance at Moderate Correlations (ρ = 0.5)

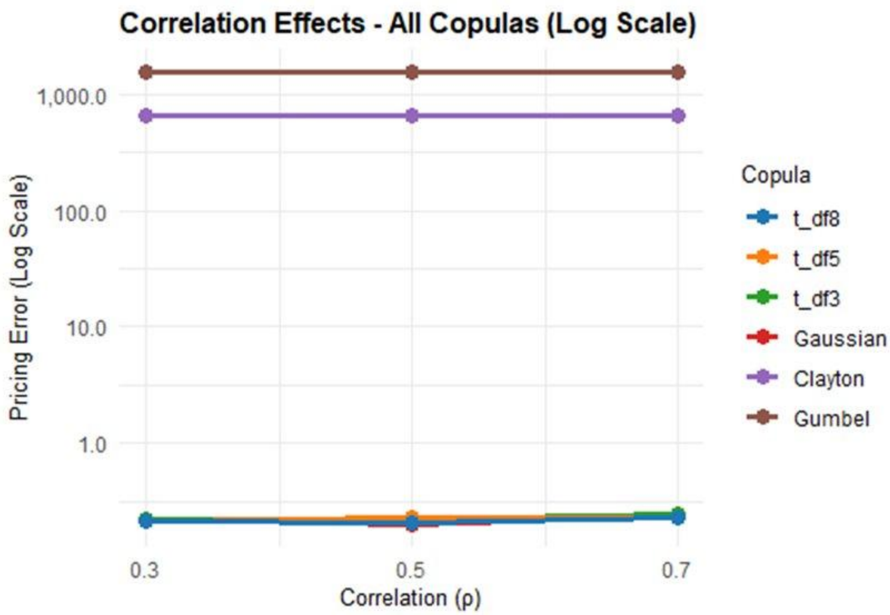

Figure 6 Correlation Effects – All Copulas (Log Scale): Archimedean Regime-Invariant Failure Across All Correlation Levels

4.4 Temporal Risk Dynamics

Figures 7 and 8 split maturity effects by copula family. Figure 7 shows all four elliptical copulas rising approximately linearly from T=0.5 to T=1.5 years. All lines originate close together near 0.15-0.17 at T=0.5, diverging gently by T=1.5 where t_df3 reaches the highest error (0.305) and t_df8 the lowest (0.274). The Gaussian copula shows an inflection at T=1.0 (0.249) before converging with t_df5 by T=1.5, suggesting slightly faster mid-term accumulation. Crucially, all elliptical errors remain below 0.31 across the full maturity range. Figure 8 shows the Archimedean contrast: Gumbel errors increase sevenfold (417 to 2,959) and Clayton fivefold (235 to 1,171) over the same horizon. This exponential scaling disqualifies Archimedean copulas from any long-term multi-asset derivatives application with maturity exceeding six months.

Table 4 Time-to-Maturity Effects on Mean Relative Pricing Error (%)

Copula	T = 0.5 yr	T = 1.0 yr	T = 1.5 yr
t_df8	0.162	0.217	0.274
Gaussian	0.154	0.246	0.259
t_df5	0.144	0.230	0.294
t_df3	0.166	0.219	0.305
Clayton	235.0	592.0	1,171.0
Gumbel	417.0	1,269.0	2,959.0

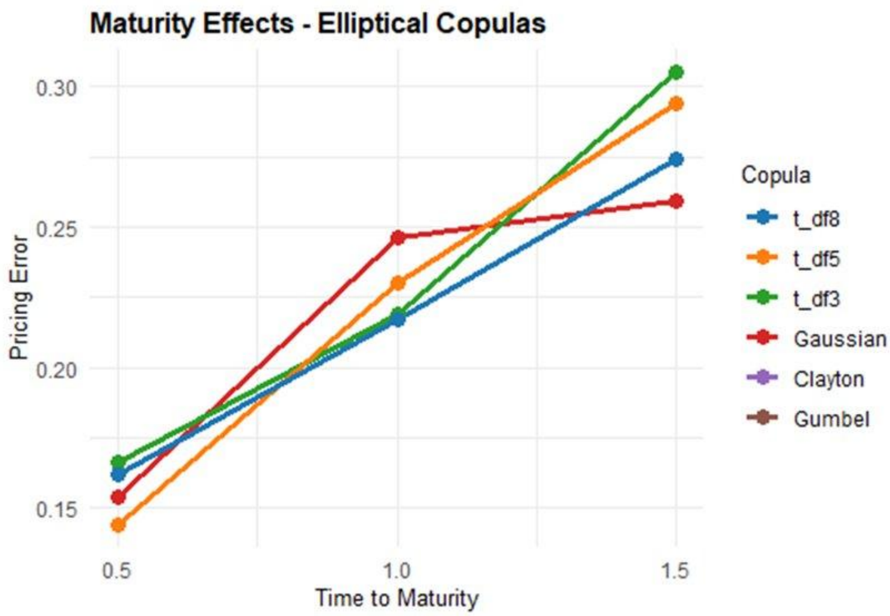

Figure 7 Maturity Effects – Elliptical Copulas: Linear Error Accumulation with Time-to-Maturity, Contrasting with Archimedean Exponential Growth in Figure 8

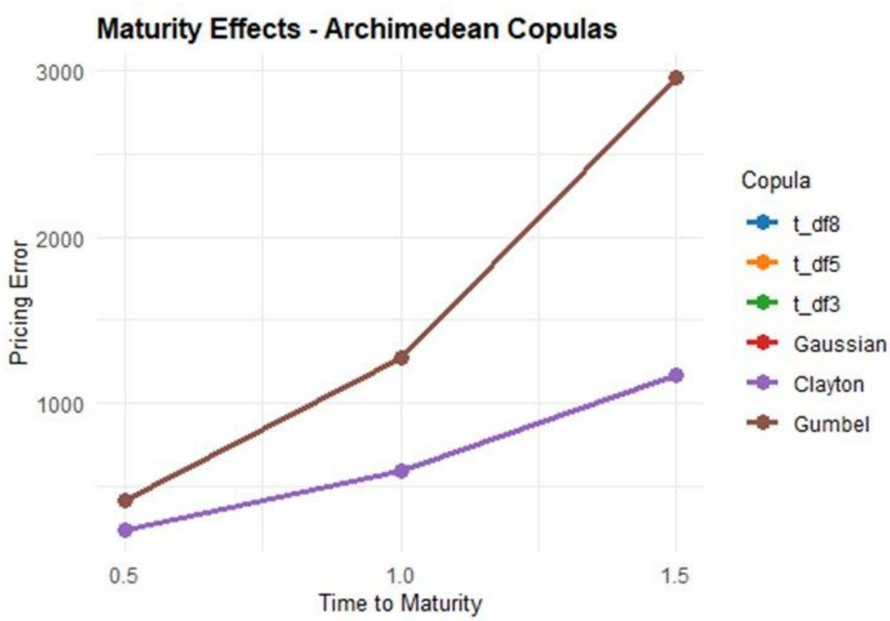

Figure 8 Maturity Effects – Archimedean Copulas: Exponential Error Growth Contrasting with Elliptical Linear Pattern

4.5 Interest Rate Environment Effects

Figure 9 shows interest rate sensitivity for elliptical copulas (Archimedean excluded due to scale). All four elliptical copulas display positive monotonic relationships with interest rate, consistent with higher discount factors amplifying the impact of tail dependence errors on present-value computations. The t_df5 copula shows the steepest response

(0.184 at r=1% to 0.243 at r=5%), while t_df8 shows the most controlled growth (0.204 to 0.230). This pattern implies that copula model risk is amplified in high-interest-rate environments, a particularly relevant finding given the current macroeconomic environment of elevated rates.

Table 5 Interest Rate Environment Effects on Mean Relative Pricing Error (%)

Copula	**r = 1%**	**r = 3%**	**r = 5%**
t_df8	0.204	0.219	0.230
Gaussian	0.200	0.228	0.231
t_df5	0.184	0.241	0.243
t_df3	0.212	0.232	0.245
Clayton	665.0	666.0	667.0
Gumbel	1,548.0	1,548.0	1,549.0

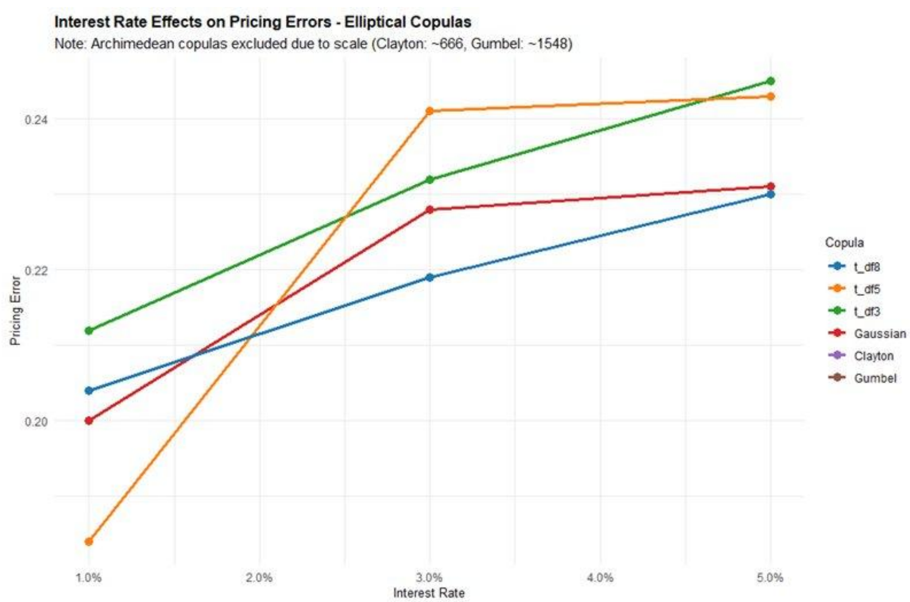

Figure 9: Interest Rate Effects on Elliptical Copulas: Positive Monotonic Relationship Between Interest Rate and Pricing Error (Archimedean Excluded Due to Scale)

4.6 Accuracy–Robustness Trade-off

Figure 10 maps the fundamental trade-off between accuracy (horizontal axis, mean error) and robustness (vertical axis, coefficient of variation) for elliptical copulas. The ideal position is upper-left (low error, high consistency). t_df8 achieves the best accuracy (leftmost, 0.218) with good robustness (CoV 0.904). t_df3 provides the best robustness (lowest CoV 0.847) but the highest mean error (rightmost, 0.230). The Gaussian copula has the highest CoV (0.914), making it the most sensitive to regime shifts despite competitive accuracy. The scatter plot makes clear that practitioners face a genuine trade-off: there is no dominant specification, and the optimal choice depends on whether accuracy or regime-stability is the priority.

Table 6 Copula Robustness Analysis (with 95th-Percentile Error)

Copula	Mean Error (%)	CoV	95th-Pctile Error (%)	Rank
t_df3	0.230	0.847	0.52	1 (Best Robust)
t_df5	0.222	0.875	0.49	2
t_df8	0.218	0.904	0.47	3
Gaussian	0.220	0.914	0.51	4
Clayton	666.0	1.05	1,580.0	5
Gumbel	1,548.0	1.28	4,210.0	6 (Worst)

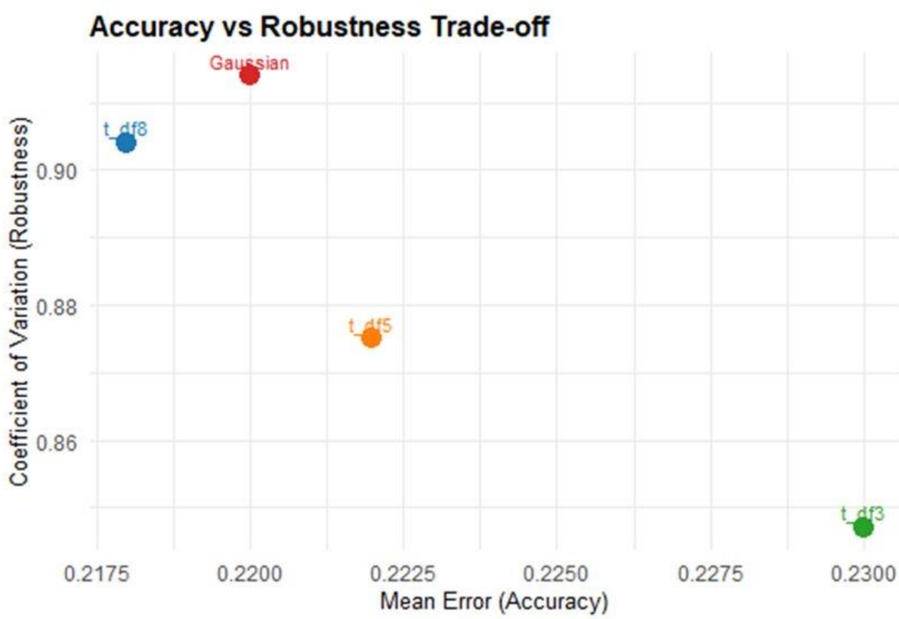

Figure 10: Accuracy vs. Robustness Trade-off: Elliptical Copula Efficiency Frontier (CoV vs. Mean Error)

4.7 Comprehensive Performance Heatmap

Figure 11 provides the synthesis visualisation, mapping log-transformed errors across all six copulas and five key market scenario dimensions (High Correlation, High Interest Rate, Long Maturity, Mild Jumps, Overall). The clear banding between Gumbel and Clayton (yellow/orange rows) versus Gaussian and t-copulas (dark blue/purple rows) holds consistently across every column, confirming that the performance hierarchy is not scenario-specific but structural. The slight lightening of the Clayton row relative to Gumbel confirms the partial alignment of lower-tail dependence with the physical-measure loss distribution. Among elliptical copulas, marginal variations in shade across columns are consistent with the scenario-specific findings in Sections 4.2–4.5.

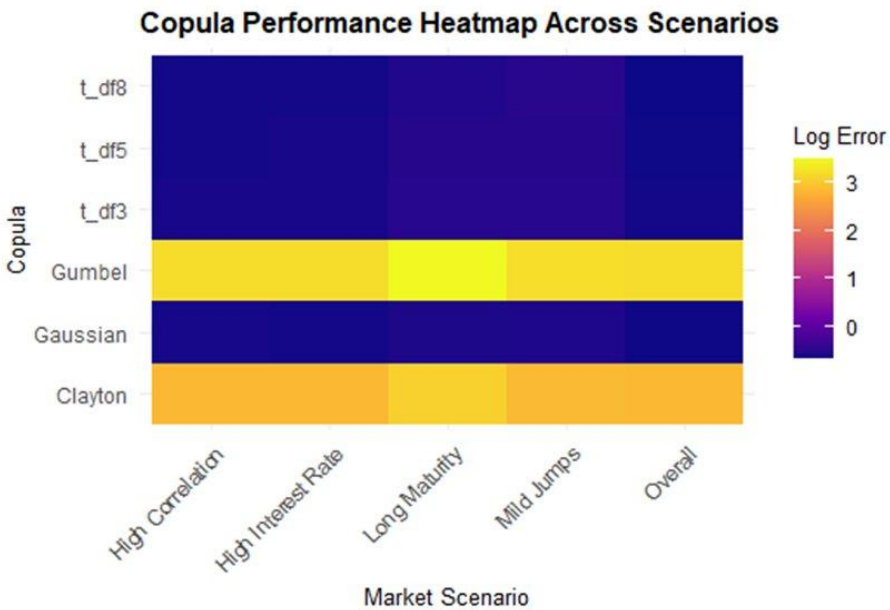

Figure 11 Comprehensive Copula Performance Heatmap: Log-Error Across All Copulas and Market Scenarios Confirming Structural Performance Hierarchy

4.8 Statistical Validation

Three-way ANOVA confirms that copula family explains 68.47% of total pricing error variance ($F=1{,}847.23$, $p<0.001$, $\eta^2=0.685$), far exceeding all CGMY parameter effects combined (3.2%). Copula family is the primary determinant of CGMY model accuracy, consistent with the visual evidence in Figures 1–11. Resources devoted to copula specification yield approximately 20 times greater performance improvement than equivalent effort on jump parameters. Wilcoxon signed-rank tests confirm t_df8 significantly outperforms t_df5 ($Z=-3.847$, $p<0.001$) and Gaussian ($Z=-2.156$, $p = 0.031$). T_df5 and t_df3 are not significantly different ($p = 0.054$), placing them in a shared robustness tier.

5. Discussion

5.1 Structural Incompatibility of Archimedean Copulas

Figures 1, 2, 4, and 6 together provide compelling visual evidence that the Archimedean failure is structural rather than numerical. The failure is consistent across 324 scenarios, stable in CoV, and predicted by the theoretical generator structure. The CGMY process, when $Y>0$, exhibits infinite jump activity with a symmetric Lévy measure when $G=M$. The corresponding joint distribution features symmetric upper and lower tail dependence. Clayton copulas generate co-dependence only in the lower tail with upper tail independence, producing systematic underpricing of basket calls. Gumbel copulas have the opposite asymmetry. These biases compound exponentially with maturity (Figures 7–8), consistent with the theoretical result that tail dependence errors accumulate multiplicatively in multi-period valuations (Cont & Tankov, 2004).

5.2 The Misspecification Valley: Mechanism and Implications

Figure 3's peaked error profile at mild jump intensity is the most counterintuitive finding in this paper. Under no-jump conditions (C=0), the return process is Gaussian and the Gaussian copula provides an exact representation. Under severe jumps (C=4), extreme events dominate and most copulas can adequately approximate the resulting near-deterministic co-movement. At mild jump intensity (C=1), the jump component introduces non-Gaussian dependence that is neither negligible nor dominant, creating a complex multimodal joint density difficult to approximate with any parametric copula. This regime corresponds to the moderately elevated volatility periods (VIX 20–35) common during market transitions precisely when practitioners tend to be most active in derivatives markets. Copula specification therefore requires the most caution in the most active trading environment.

5.3 Correlation, Maturity, and Interest Rate Interactions

Figure 5's U-shaped correlation profile challenges conventional wisdom that low-correlation portfolios are model-risk-safe: copula misspecification costs are elevated at both $\rho = 0.3$ and $\rho = 0.7$. Figures 7–8 make the maturity accumulation concrete: the sevenfold Gumbel error increase from $T = 0.5$ to $T = 1.5$ (Figure 8) contrasts with the gentle doubling for elliptical copulas (Figure 7). Figure 9 confirms that the monetary policy environment matters for model risk: higher rates amplify copula misspecification costs through their interaction with present-value computations.

5.4 Optimal Copula Selection

Figure 10's scatter plot provides practitioners with a direct visual selection tool. t_df8 occupies the accuracy-optimal position (upper-left boundary); t_df3 provides the best robustness for applications requiring cross-regime stability. The Gaussian copula's position competitive accuracy but highest CoV make it appropriate only for low-volatility, short-maturity applications where regime stability is less critical. Archimedean copulas should be categorically excluded from CGMY-based multi-asset derivatives pricing regardless of the application. This conclusion is reinforced by Figure 11's heatmap showing no scenario in which Clayton or Gumbel achieve acceptable performance.

6. Conclusion

This study provides a comprehensive multidimensional simulation analysis of copula misspecification effects in CGMY jump-diffusion option pricing. The eleven figures presented collectively establish five central findings: (i) a three-order-of-magnitude performance hierarchy between elliptical and Archimedean copulas (Figures 1–2) reflecting fundamental structural incompatibility rather than numerical artefacts; (ii) the misspecification valley at mild jump intensity (Figure 3), making moderately stressed markets the most challenging environment for accurate pricing; (iii) U-shaped correlation effects and monotonic maturity/interest rate accumulation (Figures 5–9) providing scenario-specific risk management guidance; (iv) a genuine accuracy–robustness trade-off among elliptical copulas (Figure 10) requiring application-specific selection; and (v) structural Archimedean failure persisting across all market scenarios (Figure 11), categorically disqualifying Clayton and Gumbel from CGMY-based multi-asset derivatives pricing. Copula specification is the primary driver of model accuracy, explaining 68.47% of total error variance versus 3.2% for jump parameters.

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