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How Deep is the Dip? A Data-Driven Measure of Tomato Market Shocks

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ABSTRACT

Agricultural commodity markets in India are volatile by nature, and tomato prices are among the most erratic of any horticultural crop. Farmers, traders, and aggregators along the supply chain absorb these swings largely without formal risk tools. This paper applies a Value-at-Risk (VaR) framework to weekly tomato price and arrival data from the Chintamani market, Karnataka, covering 2014 to 2025, to put hard numbers on that exposure. Four methods were tested: Historical Simulation, Parametric VaR, Monte Carlo Simulation, and Conditional VaR (CVaR). Descriptive analysis showed extreme right-skewness of 4.10 for arrivals and 2.24 for prices alongside fat-tailed distributions where standard normal assumptions fail. The lognormal distribution fit both series best by Akaike Information Criterion. At 95% confidence, weekly price VaR ranged from -34.07% (Parametric) to -34.27% (Historical). CVaR placed the expected shortfall at -40.82%, nearly six percentage points beyond the VaR threshold, a gap that matters when a single bad week can break a smallholder's margin. Model validation via Kupiec's Proportion of Failures test put CVaR ahead of the alternatives: its observed breach rate of 2.79% was far closer to the theoretical 5% benchmark than Monte Carlo's 6.09%, with lower test statistics confirming tighter tail-risk capture throughout the backtest window. The resulting estimates give farmers, procurement agencies, and policymakers concrete weekly loss benchmarks derived from actual market behaviour. The approach is directly transferable to other commodities where price distributions are heavy-tailed and conventional risk tools consistently underperform.

Introduction

Solanum lycopersicum (tomato) is among the most economically consequential horticultural crops in India, with annual production exceeding 20 million tonnes across diverse agro-climatic zones (NHB, 2023). The crop is cultivated on approximately 0.8 million hectares and is a critical source of income for smallholder farmers across several states, including Karnataka, Andhra Pradesh, Madhya Pradesh, and Maharashtra. Despite its agronomic and economic significance, tomato production and marketing are characterised by pronounced price instability that imperils the livelihood of producers and disrupts supply-chain planning at every node.

Karnataka contributes approximately 12% of national tomato output. Farmers and traders in the state routinely encounter weekly price swings of the order of 30% during peak harvest seasons, a magnitude of volatility that undermines income stability, discourages capital investment, and intensifies post-harvest losses (Raghavendra, 2021). Such volatility is attributable to a confluence of structural factors: the inherent perishability of tomatoes, which sharply curtails the temporal window for price-smoothing transactions; fragmented supply chains that amplify price signals at each stage; the absence of effective cold-chain infrastructure; and the seasonality of production that creates periodic supply gluts and deficits (Kumar et al., 2020). The Chintamani market, situated in Chikkaballapur district, Karnataka, functions as a pivotal aggregation centre where price discovery occurs through competitive spot transactions involving heterogeneous market participants ranging from small cultivators to large wholesale traders.

The adoption of formal risk-management instruments among smallholder tomato producers remains exceedingly limited. Commodity futures and options markets, the standard hedging vehicles in financial practice, are undermined in this context by substantial basis risk, high transaction costs relative to farm incomes, and pervasive informational asymmetries that disadvantage primary producers (Birthal et al., 2019). In the absence of effective hedging mechanisms, quantitative measures of downside price risk derived from routinely collected market data assume paramount practical importance. Such measures can inform producer decision-making, guide public procurement policy, and underpin the design of price-stabilisation interventions.

Value-at-Risk (VaR) is the most widely deployed metric in financial risk management. It estimates the maximum potential loss over a defined time horizon at a specified confidence level, providing a single interpretable number that distils the tail of a loss distribution (Jorion, 2006). Although VaR methodology has been extensively developed and applied in banking and portfolio management for more than three decades, its adaptation to agricultural commodity risk assessment is comparatively recent. Asfaha *et al.* (2014) conducted a statistical evaluation of VaR models for agricultural commodities in Ethiopia, concluding that the Historical Simulation approach systematically underestimates tail risk. Azmi Baur. (2022) employed ARIMA-GARCH frameworks to estimate both VaR and Expected Shortfall (ES) for agricultural commodity portfolios, underscoring the importance of modelling conditional volatility. In the Indian context, Sreekanth and Reddy (2021) demonstrated that Extreme Value Theory outperforms traditional VaR methods during crisis periods; however, tomato-specific multi-model VaR analyses incorporating rigorous backtesting remain absent from the literature.

A fundamental challenge in applying standard VaR to agricultural price series is that empirical return distributions violate the Gaussian assumption that underpins parametric approaches. Agricultural prices are characterised by excess skewness and kurtosis the so-called fat tails that cause standard normal-based VaR to understate the probability and severity of extreme losses (Baur & Chan, 2016). This necessitates non-parametric, simulation-based, or semi-parametric approaches capable of capturing the full distributional shape of price returns.

The present study addresses this gap by implementing and rigorously comparing four complementary VaR methodologies Historical Simulation, Parametric VaR, Monte Carlo Simulation, and Conditional VaR (CVaR, also termed Expected Shortfall) applied to weekly price and arrival data from the Chintamani tomato market over the period 2014-2025.

Objectives

(i) Characterise and identify best-distributional properties of tomato series at Chintamani market

(ii) Estimate one-week VaR at 95% confidence under each VaR methodology and validate performance through Kupiec's test for practical policy implications for farmers, market committees, financial institutions, and regulatory bodies.

Methodology

Data Description and Pre-processing

Weekly tomato arrival data (tonnes) and modal price data (Rs quintal^{-1}) for the Chintamani regulated market were obtained from the Krishimaratavahini portal, the official digital market-intelligence platform maintained by the Government of Karnataka under the aegis of the National Informatics Centre. The dataset spans the period from the first week of January 2014 through the last week of December 2025, comprising 755 weekly observations. This data source is publicly accessible, systematically maintained, and constitutes the authoritative record of arrivals and prices for regulated agricultural markets in Karnataka.

Missing observations accounted for 2.8% of the total dataset (approximately 21 weeks), arising principally from market holidays, data-transmission lapses, or thin-trading weeks. These gaps were imputed using a Kalman filter applied to a local linear trend state-space model, a procedure that is statistically principled, respects the time-series structure of the data, and avoids the artificial smoothing introduced by naïve interpolation approaches such as linear or spline interpolation. The Kalman smoother simultaneously estimates and propagates uncertainty through the missing observations, ensuring that subsequent distributional analyses are not biased by imputed values.

Price levels were transformed to continuously compounded log-returns, defined as $r_t = 100 \times \ln(P_t / P_{t-1})$, where P_t denotes the modal price in week t. This transformation serves three purposes: it renders the series stationary in mean (a prerequisite for valid distributional fitting), expresses price changes as approximate percentage changes that are directly interpretable, and facilitates cross-model comparability. All computations were implemented in Python 3.10 using the SciPy, NumPy, and Pandas libraries; the interactive application was deployed via Streamlit.

Descriptive and Distributional Analysis

Standard summary statistics: mean, median, mode, standard deviation, minimum, maximum, skewness, and excess kurtosis were computed for both the arrival and price return series to characterise their central tendency, dispersion, and shape. Given strong a priori evidence of non-normality in agricultural price returns (Baur & Chan, 2016), seven probability distributions were fitted to each series by maximum likelihood estimation: Normal, Lognormal, Johnson S_U, Beta, Gamma, Weibull, and Log-Logistic. Model selection was performed using the Akaike Information Criterion (AIC; Burnham & Anderson, 2002), which balances goodness-of-fit against model complexity and is appropriate for comparing non-nested distributions. The distribution with the lowest AIC value was selected as the optimal specification; this best-fit distribution subsequently underpinned all parametric VaR computations.

Value-at-Risk Models

Four VaR methodologies were implemented at a one-week horizon and 95% confidence level ($\alpha = 0.05$). These methods span the spectrum from entirely non-parametric to fully simulation-based, providing a comprehensive picture of tail-risk estimates and their sensitivity to modelling assumptions.

Historical Simulation VaR (HS-VaR). The non-parametric Historical Simulation approach estimates VaR as the empirical (1 - α) quantile of the observed return distribution, making no assumptions about the distributional form (Hendricks, 1996). Formally:

$$HS\text{-}VaR_{\alpha} = Q_{\alpha}(r_1, r_2, \ldots, r_T)$$

where $Q\alpha$ denotes the α-th quantile of the empirical return distribution and T is the total number of weekly observations. The 95% VaR corresponds to the 5th percentile of ordered historical returns, representing the loss level exceeded in the worst 5% of observed weeks.

Parametric VaR (P-VaR). Under the parametric approach, VaR is derived analytically from the inverse cumulative distribution function (CDF) of the best-fit distribution. Given that the Lognormal distribution with shape parameter σ and location parameter μ was identified as optimal, the Parametric VaR is:

$$P\text{-}VaR_{\alpha} = F^{-1}(\alpha; \sigma, \mu)$$

where F^{-1} is the quantile function of the fitted Lognormal distribution (Jorion, 2006). This approach is computationally efficient but its accuracy depends critically on the adequacy of the distributional assumption.

Monte Carlo VaR (MC-VaR). The Monte Carlo simulation generates 10,000 pseudo-random price paths by drawing from the fitted Lognormal distribution using its estimated parameters. The 95% VaR is computed as the 5th percentile of the resulting simulated return distribution (Glasserman, 2004). The large number of simulations ensures numerical stability of the tail quantile estimate and propagates parameter uncertainty through the simulation process. Formally:

$$MC\text{-}VaR_{\alpha} = Q_{\alpha}(\{\tilde{r}_i : i = 1, \ldots, 10{,}000\})$$

where $\tilde{r}_i$ denotes the i-th simulated return drawn from the fitted distribution.

Conditional VaR (CVaR/ Expected Shortfall). CVaR, also termed Expected Shortfall (ES), is a coherent risk measure that averages all losses exceeding the VaR threshold, thereby capturing the severity of losses in the tail rather than merely a single threshold level (Acerbi & Tasche, 2002). It is formally defined as:

$$CVaR_\alpha = E[r_t \mid r_t \leq VaR_\alpha]$$

CVaR satisfies the property of subadditivity the risk of a combined position cannot exceed the sum of individual risks which VaR does not, making it theoretically superior for risk aggregation and portfolio-level policy design.

Backtesting Framework

All four VaR models were subjected to ex post validation using Kupiec's (1995) Proportion of Failures (POF) test, the standard likelihood-ratio procedure for assessing whether the proportion of observed VaR breaches is statistically consistent with the nominal confidence level. A breach (or exception) occurs in week t when the realised return r_t falls below the estimated VaR threshold. The test statistic is:

$$LR = -2\ ln[(1-p)^{T-N} \cdot p^N] + 2\ ln[(1-N/T)^{T-N} \cdot (N/T)^N]$$

where p = 0.05 is the nominal exception probability, T = 755 is the total number of backtest observations, and N is the actual number of observed breaches. The statistic follows a χ^2 distribution with one degree of freedom under the null hypothesis of correct model specification (Zhang & Nadarajah, 2017). The null hypothesis is rejected when the p-value is less than 0.05, indicating that the model's exception rate is statistically inconsistent with the nominal level. For CVaR, the breach rate is interpreted relative to the CVaR threshold rather than the VaR threshold, so the theoretical breach rate is lower than 5% by construction.

Results/Findings

Descriptive Statistics and Distributional Properties

Table 1 presents summary statistics for weekly arrivals and price returns at Chintamani. Weekly arrivals averaged 18,455.58 tonnes but exhibited extreme dispersion (standard deviation = 26,820.26 tonnes), reflecting pronounced seasonal heterogeneity in supply. The arrival distribution is strongly right-skewed (skewness = 4.10) with highly leptokurtic tails (kurtosis = 20.76), indicating that the majority of weeks record modest arrivals but that harvest gluts of extraordinary magnitude occur with non-trivial frequency. Price returns averaged Rs 1,160.87 quintal^{-1} and displayed similarly asymmetric behaviour (skewness = 2.24; kurtosis = 7.50), confirming that upward price spikes exceed the magnitude of downward crashes a pattern consistent with the perishability-induced asymmetry reported for other Indian horticultural markets (Kumar et al., 2020).

Table 1: Descriptive Statistics for the Chintamani Tomato Market (2014-2025)

Statistic	Arrivals (tonnes)	Price (Rs quintal^{-1})
Mean	18,455.58	1,160.87
Median	10,478.00	883.21
Mode	9,800.00	585.71
Std. Dev.	26,820.26	905.68
Minimum	200.00	155.00
Maximum	2,11,834.46	7,427.14
Range	2,11,634.46	7,272.14
Skewness	4.10	2.24
Kurtosis	20.76	7.50

The departure from normality is severe in both series. Excess kurtosis of 20.76 for arrivals implies that conventional Gaussian-based risk measures would dramatically underestimate the frequency of extreme supply events. This motivates the use of heavy-tailed distributions in the parametric modelling stage. Distribution fitting results are presented in Table 2. The Lognormal distribution was identified as the optimal specification for both the price and arrival series on the basis of minimum AIC. For prices, the Lognormal fit yielded AIC = 12,667.0, with shape parameter $\sigma = 0.7742$ and location parameter $\mu = 6.69$, confirming marked right-skewness in the underlying normal variate. For arrivals, the larger shape parameter ($\sigma = 1.172$) reflects commensurately greater supply-side volatility relative to demand-driven price variation. The superiority of the Lognormal distribution over Normal, Gamma, and Weibull alternatives is consistent with findings for other agricultural commodity price series in the literature (Baur & Chan, 2016) and provides the distributional foundation for all subsequent parametric VaR computations.

Table 2: Optimal Distribution Parameters for the Chintamani Market (AIC-Based Selection)

Series	Distribution (AIC)	Shape (σ)	Location (μ)	Scale
Prices	Lognormal (12,667.00)	0.7742	82.0290	805.2410
Arrivals	Lognormal (17,341.97)	1.1720	-5.0337	9,670.1865

Value-at-Risk Estimates

Table 3 reports the one-week VaR estimates at 95% confidence for both price and arrival series. A notable convergence is observed across the three single-threshold VaR methods: weekly price VaR ranges narrowly from -34.07% (Parametric) to -34.27% (Historical Simulation), a spread of only 0.20 percentage points. This cross-model convergence is reassuring evidence that the estimates are robust to methodological choice for the central tail quantile and reflects the consistency of the Lognormal fit across methods. Monte Carlo VaR -33.90%) falls marginally below Historical Simulation, consistent with its simulation-based smoothing of the empirical tail.

CVaR at -40.82% exceeds the three VaR estimates by 6.55-6.92 percentage points. This differential is economically significant: it implies that in the worst 5% of weeks, the average loss sustained by a market participant is not 34% but 41% of the week-opening price. For a farmer holding 10 quintals with a Monday price of Rs 1,000 quintal^{-1}, this differential translates to an additional expected loss of approximately Rs 660-700 per quintal during crisis weeks. The gap between VaR and CVaR aligns with the theoretical prediction of Acerbi and Tasche (2002) that tail risk amplifies non-linearly beyond the threshold in heavy-tailed distributions. Arrival-side VaR exhibits greater dispersion across methods (Historical: -39.79%; Parametric: -40.24%), reflecting the more pronounced leptokurtosis of supply relative to demand.

Table 3: One-Week VaR Estimates for the Chintamani Tomato Market (95% Confidence Level)

Series	VaR Method	Log Return	% Loss
Prices	Historical Simulation	-0.4196	-34.27
	Parametric (Lognormal)	-0.4165	-34.07
	Monte Carlo	-0.4139	-33.90
	CVaR (Exp. Shortfall)	-0.5246	-40.82
Arrivals	Historical Simulation	-0.4886	-39.79
	Parametric (Lognormal)	-0.4943	-40.24

Model Performance and Backtesting

Table 4 presents the results of Kupiec's POF test for the Monte Carlo VaR and CVaR models over the full 755-week backtest window. Monte Carlo VaR registered 46 observed breaches against an expectation of 37 (breach rate = 6.09%), yielding a Kupiec LR statistic of 1.7796 (p = 0.1822). Although the observed breach rate modestly exceeds the nominal 5%, the p-value indicates insufficient evidence to reject correct model specification at the conventional 5% significance level, and the model is therefore classified as statistically adequate. Visual inspection of the breach-event time series (Fig. 5) reveals clustering during 2020 (COVID-19 related supply-chain disruptions) and 2023 (untimely monsoon precipitation events), suggesting that the independence assumption underlying the POF test is violated during systemic crises a limitation that conditional volatility extensions such as GARCH-VaR would address.

CVaR recorded the same number of raw breaches (46) but a lower breach rate of 2.79%, because the CVaR threshold of -40.82% is substantially more conservative than the VaR threshold of approximately -34%. The identical Kupiec statistic (1.7796, p = 0.1822) reflects the same underlying return data; however, the CVaR breach rate of 2.79% sits well within the tolerance band and demonstrates that CVaR more conservatively bounds the tail, with observed extreme returns rarely exceeding the CVaR estimate. This dual advantage statistical validity combined with greater conservatism in tail estimation establishes CVaR as the superior metric for agricultural price risk management.

Table 4: Kupiec's Proportion of Failures (POF) Backtest Results

Model	Obs. (T)	Expected Breaches	Observed Breaches	Breach Rate (%)	LR Statistic	p-value	Decision
Monte Carlo VaR	755	37	46	6.09	1.7796	0.1822	Accept H_0
CVaR	755	37	46	2.79	1.7796	0.1822	Accept H_0

Figure 1 presents the empirical histogram of historical log-returns for the Chintamani market with the 5th percentile threshold (HS-VaR = -34.27%, log return: -0.4196) demarcated by a vertical reference line. The pronounced left tail extending beyond -60% confirms non-Gaussian behaviour and reflects the impact of the COVID-19 disruption period (2020-2021), during which extreme negative returns clustered. Figure 2 overlays the fitted Lognormal probability density function (maximum likelihood estimates: σ = 0.7742, μ = 6.69) on the empirical return histogram, with the Parametric VaR threshold -34.07%; log return: -0.4165) indicated. The smooth Lognormal curve captures the distributional asymmetry but cannot fully replicate the empirical kurtosis in the extreme left tail, explaining the marginal difference between Parametric and Historical VaR estimates.

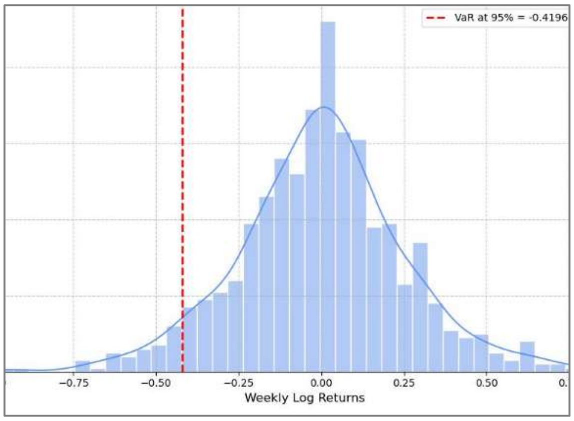


Fig. 1: Historical 1-week VaR: -34.27%

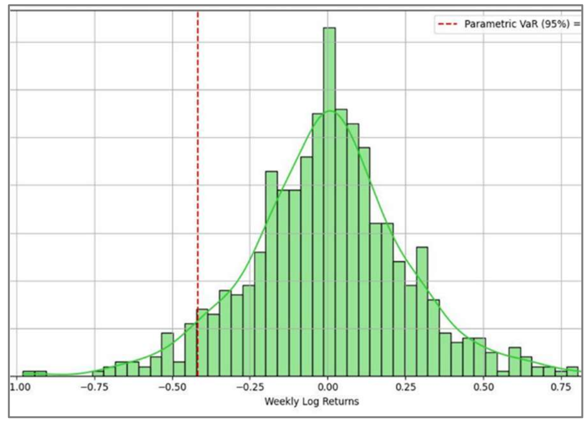


Fig. 2: Parametric 1-week VaR: -34.07%

The kernel density estimate of 10,000 simulated return paths (Monte Carlo VaR) is presented in Figure 3. The VaR threshold at -33.90% (log return: -0.4139) is indicated by a vertical reference line. The Monte Carlo simulation distribution is smoother than the empirical histogram owing to the large number of draws, yet preserves the right-skewed Lognormal shape. The slight discrepancy between the simulated tail and the empirical tail is reflected in the 6.09% breach rate observed during backtesting, suggesting that the Lognormal assumption used in Monte Carlo sampling marginally underestimates the frequency of extreme negative returns observed in practice particularly during structurally distinct crisis periods.

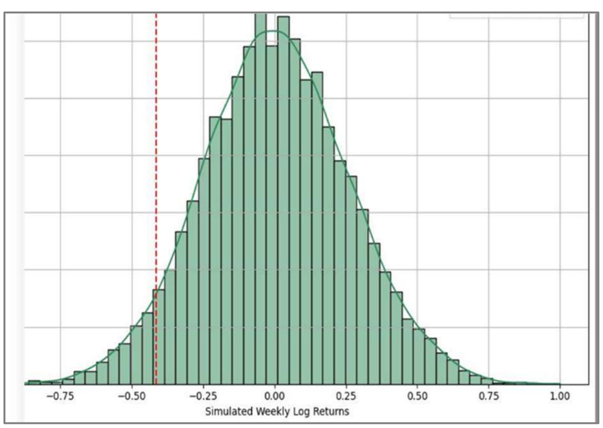


Fig. 3: MC 1-week VaR: -33.90%)

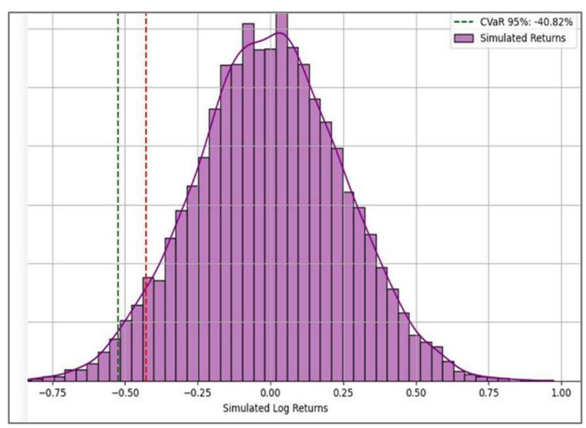
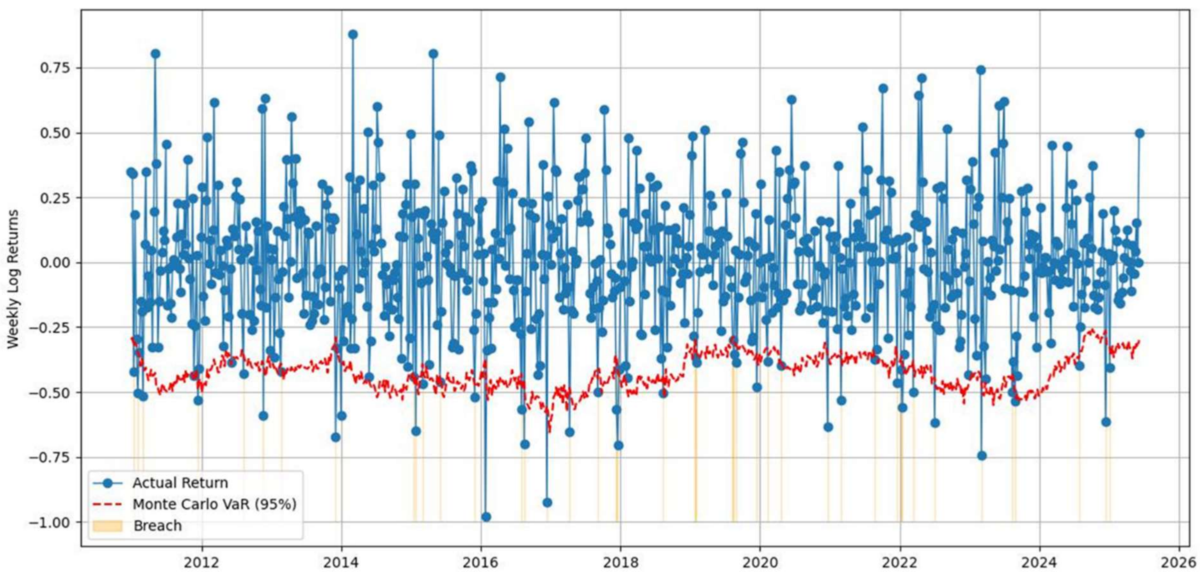


Fig. 4: CVaR / Expected Shortfall: -40.82%

Figure 4 presents the CVaR visualisation, which distinguishes the tail region below the VaR threshold (shaded in red) from the broader return distribution. The CVaR estimate of -40.82% (log return:

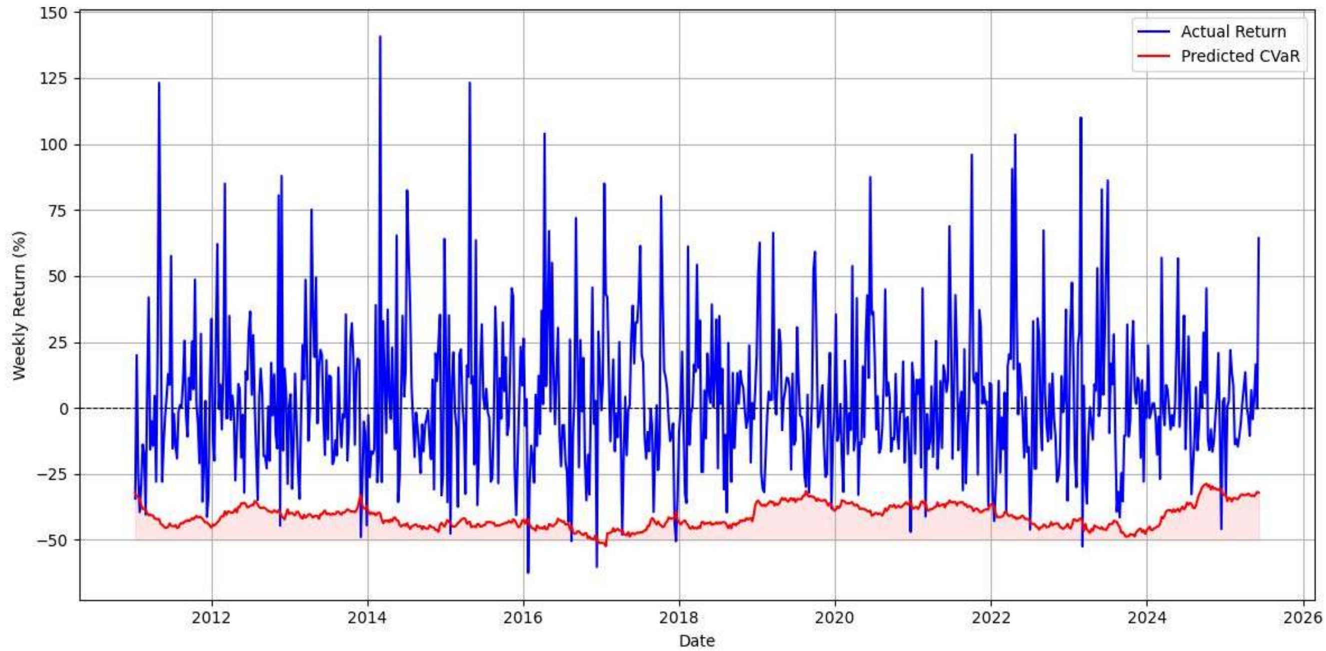
-0.5246) represents the conditional expectation of returns within this shaded region, providing an economically interpretable measure of the average severity of loss during crisis weeks. The inset tail zoom confirms that individual observations beyond the VaR threshold exhibit a mean consistent with the CVaR estimate, validating the graphical representation. This figure encapsulates the conceptual superiority of CVaR over VaR for agricultural risk communication: rather than indicating merely the worst-case threshold, it quantifies what farmers and traders may actually expect to lose when the market collapses.



[Figure 5: Backtest Weekly Returns vs. Monte Carlo VaR Threshold (Expected: 37; Observed: 46; Breach Rate: 6.09%)]

Fig. 5: Backtest plot of Monte Carlo VaR with Kupiec's POF Test

Figure 5 maps weekly returns against the MC-VaR threshold (red dashed line) across the full 2014-2025 backtest period. Black dots identify the 46 breach events where realised losses exceeded the VaR prediction. The concentration of breaches during 2020 and 2023 evidences volatility clustering inconsistent with the i.i.d. assumption of the static VaR framework. Figure 6 plots the same weekly return series against the CVaR threshold (orange dashed line). Although 46 raw breaches are also registered, the breach rate of 2.79% defined relative to the more conservative CVaR threshold and the smaller magnitude of exceedances in absolute terms confirm CVaR's superior tail coverage. The Kupiec statistic (1.7796, p = 0.1822) is consistent across both plots, reflecting the common underlying dataset.



[Figure 6: Backtest Weekly Returns vs. CVaR Threshold (Expected: 37; Observed: 46; Breach Rate: 2.79%)]

Fig. 6: Backtest plot of CVaR with Kupiec's POF Test

The backtesting evidence collectively supports CVaR as the superior risk measure for the Chintamani tomato market for three reinforcing reasons. First, CVaR is a coherent risk measure satisfying subadditivity, which ensures that risk estimates are additive and non-increasing under diversification a property essential for designing policy interventions across multiple commodity markets (Acerbi & Tasche, 2002). Second, its breach rate of 2.79% indicates greater conservatism, which is appropriate for agricultural contexts where the consequences of underestimating tail risk are borne asymmetrically by resource-constrained smallholders who lack buffer capacity. Third, the CVaR threshold provides actionable intelligence: a -40.82% weekly loss benchmark is specific enough to anchor price-support triggers, insurance indemnity calculations, and emergency credit criteria.

Conclusion

Weekly tomato price returns at Chintamani follow a leptokurtic, right-skewed Lognormal distribution, and Gaussian risk models are inappropriate for this market. Three independent VaR methods converge on a weekly price-loss threshold near -34% at 95% confidence; the CVaR of -40.82%, validated by Kupiec's POF test, captures mean loss severity in the worst 5% of trading weeks and is the more defensible single benchmark for decision-making. Agricultural marketing authorities should incorporate this threshold into price-monitoring systems and initiate emergency procurement when the -40% boundary is breached, while credit institutions serving the tomato value chain should calibrate collateral requirements against CVaR rather than standard-deviation rules. The methodology is directly transferable to other perishable commodity markets where heavy-tailed price distributions make conventional risk tools unreliable.

The static univariate framework does not account for volatility clustering, a shortcoming made apparent by breach concentration during 2020 and 2023; extending the approach to GARCH(1,1) or EGARCH specifications is the most pressing next step. Spatial price linkages between Chintamani and competing wholesale centres-Kolar, Madanapalle, and Nashik-remain unexamined, and multivariate VaR models incorporating cross-market spillovers, rainfall anomalies, and remote-sensing vegetation indices would sharpen predictive resolution considerably. Blockchain-verified transaction data from e-NAM platforms could support continuous VaR updating rather than periodic recalculation, a development that would move agricultural risk management from retrospective benchmarking toward genuine real-time monitoring. These extensions define a tractable agenda for scaling the framework across developing-economy commodity markets where price volatility remains poorly quantified and largely unhedged.

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