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Rupel Nargunam* Sudheesh K. K.†

Abstract

This research introduces a nonparametric approach for estimating tail conditional variance (TCV) at the p-th quantile through the use of Jackknife Empirical Likelihood (JEL). TCV functions as a second-moment indicator of tail risk, offering enhanced understanding of the variability of extreme losses, surpassing traditional scalar measures such as Conditional Value-at-Risk (CVaR). By utilizing jackknife pseudo-values within an empirical likelihood framework, we are able to develop robust confidence intervals for TCV without the necessity of specific distributional assumptions—an essential benefit when addressing financial returns characterized by heavy tails and skewness. The proposed methodology is applied to mean-variance portfolio analysis, facilitating the construction of efficient frontiers that explicitly incorporate downside tail volatility. The findings indicate that the integration of JEL-based inference enhances both the interpretability and statistical robustness of portfolio risk evaluations, particularly in scenarios marked by model uncertainty and limited data in the tail.

Keywords: Tail Conditional Variance, Jackknife Empirical Likelihood, Confidence Interval, Mean Variance Portfolio Analysis

JEL codes: G11, C13, C14, C15

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1 Introduction

Risk measures are very important tools in actuarial science and finance. The objective of an actuary or risk manager is to choose a risk measure that is suitable for the purpose of internal management or for external regulatory control. The tail behavior of loss distributions may be a subjective issue depending on the actuary's (or risk manager's) experience and/or preference.

Traditional portfolio theory (Markowitz, 1952) uses variance as a risk measure. However, this symmetric measure penalizes both gains and losses, prompting the development of tail-focused metrics that better align with investor concerns. (Rockafellar and Uryasev, 2000) introduced CVaR as a coherent alternative to Value-at-Risk (VaR), laying the groundwork for more informative tail-based portfolio risk metrics. Tail Conditional Variance (TCV), like Conditional Value-at-Risk (CVaR), quantifies the dispersion of extreme losses. Although TCV is less common in practice, it provides richer information about tail volatility than scalar measures like CVaR. Further emphasizing the importance of tail analysis, Happersberger (2020) employed Extreme Value Theory (EVT) to estimate and protect against severe portfolio losses. While not directly employing empirical likelihood, the work underlines the growing focus on tail risk protection in modern risk management. However, estimating tail behavior from finite samples poses a challenge. (Peng and Qi, 2006) developed empirical likelihood-based confidence intervals specifically for the tail index of heavy-tailed distributions. Their nonparametric framework was pivotal in enabling reliable inference in tail estimation, serving as a foundation for later applications of empirical likelihood to risk metrics like CVaR and TCV. This innovation makes it possible to create confidence intervals around tail measures, even when distributional assumptions break down. Their work laid the groundwork for applying EL to tail-focused risk estimation, such as TCV. Jackknife methods offer a classical approach to estimate uncertainty without assuming a distribution. Originally proposed by (Quenouille, 1949) and expanded by (Tukey, 1958), jackknife resampling is used to construct pseudo-values which approximate the influence of each observation. Efron and Tibshirani (1993) showed how jackknife pseudo-values can be integrated into robust inference pipelines, especially when combined with nonparametric likelihood. Jing et al. (2009) applied JEL successfully to a wide range of estimators, showing its robustness and finite-sample efficiency.

Motivated by these recent developments in risk measures, we develop JEL based inference to construct confidence intervals for TCV at the $p-$th quantile which is distribution free. Empirical likelihood (EL) is a non-parametric inference tool which makes use of likelihood principle. This inference procedure was first used by Thomas and Grunkemeier (1975) to obtain the confidence interval for survival probability when the data contain censored observations. Pioneering papers by Owen (1990) for finding the confidence interval of regression parameters developed EL into a method that has wide applications in many statistical areas. Consequently, we maximize the non-parametric likelihood function subject to some constraints. When the constraints are linear, the maximization of the likelihood is not difficult. However, when the constraints are based on nonlinear statistics such as U-statistics with higher degree (≥ 2) kernel the implementation of EL becomes challenging. To overcome this difficulty, Jing et al. (2009) introduced the jackknife empirical likelihood (JEL) inference, which combines two of the popular non-parametric approaches namely, the jackknife and the EL approach.

In this paper, we extend the idea of EL-based confidence intervals for the tail index (Peng and Qi, 2006) to quantifying tail risk measures in portfolio analysis (Happersberger, 2020) and attempt to develop a non-parametric JEL estimate of confidence interval for the sample $p-$ quantile for portfolio risk.

The proposed measure is tested using a numerical example to determine the portfolio risk following the mean-variance portfolio theory (Markowitz, 1952). The rest of the paper is structured as follows: In Section 2, we construct the confidence interval for tail conditional variance using JEL. In Section 3, we present the results of a simulated study for the proposed method. In Section 4, we implement the method using real-time data. Section 5 concludes the study.

2 Tail conditional variance

This section describes the construction of JEL-based confidence interval for tail conditional variance (TCV) at the p-th quantile.

2.1 JEL inference for tail conditional variance

Let X denote a loss random variable. The Conditional Tail Expectation (CTE) of X at the confidence level $l00p\%$, denoted CTE_p is the expected loss given that the loss exceeds the $l00p$ percentile of the distribution of X

$$CTE_p(X) = E[X|X > \zeta_p],$$

where ζ_p is the p quantile defined as $\zeta_p = \inf\{x : F(x) \geq p\}$.

For measuring the variability along the right tail of its distribution Valdez (2004) suggested the tail conditional variance(TCV) risk measure defined as:

$$\theta_p = TCV_p = E[(X - E[(X)^2|X > \zeta_p]]. \quad (1)$$

Next, we express TCV_p in a different form, which enables us to find a U-statistics based estimator of TCV_p. Consider

$$\begin{aligned}
\theta_p &= TCV_p = E((X - E[(X)^2)|X > \zeta_p) = \int_{\zeta_p} (x-\mu)^2 \frac{f(x)dx}{1-p} \\
&= \frac{1}{1-p}\int_{\zeta_p}^{\infty} (x-\mu)^2 dF(x) \\
&= \frac{1}{1-p}\int_{0}^{\infty} (x-\mu)^2 I(x > \zeta_p) dF(x) \\
&= \frac{1}{1-p}\int_{0}^{\infty} (x - 2x\mu + \mu^2) I(x > \zeta_p) dF(x) \\
&= \frac{1}{1-p}[E(X_1^2 I(X_1 > \zeta_p)) - 2\mu E(X_1 I(X_1 > \zeta_p)) + \mu^2(1-p)].
\end{aligned}$$

The above equation can be written as

$$\theta_p = TCV_p = \frac{1}{1-p}[E(X_1^2 I(X_1 > \zeta_p)) - 2E(X_1X_2 I(X_1 > \zeta_p)) + E(X_1X_2)(1-p)]. \quad (2)$$

Let $X_1, X_2, \dots, X_m; m \geq 2$ be i.i.d random variables with distribution P and there exists a real valued measurable function $h(x_1, x_2, \dots, x_m)$ such that, $E_p[h(X_1, X_2, \dots, X_m)] = \theta_p$ where θ_p is an estimable parameter.

Also, h is assumed to be a symmetric function of its arguments, because f is an unbiased estimator of θ_p, then the average of f applied to all permutations of the variables is still unbiased and is in addition symmetric.

That is

$$h(x_1, x_2, \dots, x_m) = \frac{1}{m!}\sum_{\pi \in \prod_m} f((x_1, x_2, \dots, x_m).$$

where the summation is over the group of $\prod_m$ of all permutations of an $m-$ vector, is obviously symmetric in all the arguments and has the same expectation under P as does f.

For a sample $X_1, X_2, \dots, X_m$ of size $n \geq m$, from a distribution P and a real-valued measurable function $h(x_1, x_2, \dots, x_m)$, a U-statistic with kernel h is defined as:

$$U_n = U_n(h) = \frac{(n-m)!}{n!} \sum_{P_{m,n}} h(X_{i_1}, X_{i_2}, \ldots, X_{i_m})$$

Here, from Equation(2), we see that $m = 2$. Hence, the corresponding $U-$ statistic measure is

$$\widehat{\theta}_p = U_n^{(2)} = \frac{1}{\binom{n}{2}} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} h(X_i, X_j), \tag{3}$$

which is based on the symmetric kernel,

$$h(X_i, X_j) = \frac{[X_1^2 I(X_1 > \zeta_p)] + [X_2^2 I(X_2 > \zeta_p)]}{2(1-p)} \\ \frac{-2X_1X_2 I(X_1 > \zeta_p) - 2X_1X_2 I(X_2 > \zeta_p) + 2(1-p)X_1X_2}{2(1-p)}.$$

We then study the asymptotic properties of $\widehat{\theta}_p$.

Theorem 1 (Consistency)

By definition, $\widehat{\theta}_p$ is a consistent estimator of θ_p.

Theorem 2 (Convergence in distribution)

If we want a confidence interval for θ_p, then we need the distribution of $\widehat{\theta}_p$. Suppose that $E(h^2(X_1, X_2, \ldots, X_m)) < \infty$, then at $n \to \infty$, $\sqrt{n}(\theta_p - \widehat{\theta}_p)$ converges in distribution to a Gaussian random variable with mean 0 and variance $m^2\sigma^2$, here the variance is $4\sigma^2$ and $\sigma^2 = Var(E(h(X_1, X_2)|X_1))$.

2.1.1 Estimation of confidence interval

Let $\widehat{\sigma}^2$ be a consistent estimator of σ^2. Using Theorem 1, we can obtain a normal based confidence interval $\widehat{\theta} \pm \widehat{\sigma} Z_{\frac{\alpha}{2}}$, where $Z_{\frac{\alpha}{2}}$ is the upper $\alpha-$ percentile point of a standard normal random variate. As finding a consistent estimator of σ^2 for most distributions is not easy and the construction of a normal based confidence interval is very difficult. An alternative method of estimation is using the empirical likelihood. So, from Equation (3) it is evident that it is a $U-$ statistic measure with degree 2, hence the empirical likelihood estimation has non-linear constraints, which make implementation difficult. Since $\widehat{\theta}_p$ is a $U-$ statistics-based estimator with kernel of degree greater than one, which results in nonlinear constraints in the optimization problem associated with empirical likelihood inference. This makes the computation and implementation of the empirical likelihood method very tedious and leading to motivation of constructing JEL based confidence interval for $\widehat{\theta}_p$. The JEL method is the combined version of jackknife and empirical likelihood method. The key idea of the JEL method is to turn the statistic of interest into a sample mean based on the jackknife pseudo-values Jing et al. (2009).

2.1.2 Derivation of JEL measure for θ_p

Here, the jackknife pseudo-values for θ_p are given by:

$$V_k = n\widehat{\theta}_p - (n-1)\widehat{\theta}_{p,k}; \qquad k = 1, 2, \ldots, n,$$

where $\widehat{\theta}_{p,k}$ is the estimator of θ_p obtained using $(n-1)$ observations $X_1, X_2, \ldots,$ X_{k+1}; $k = 1, 2, \ldots, n$. The jackknife estimator, $\widehat{\theta}_{p,jack}$ of $\widehat{\theta}_p$ is the average of the pseudo-values and is defined as:

$$\widehat{\theta}_{p,jack} = \frac{1}{n}\sum_{k=1}^{n} \widehat{V}_k \tag{4}$$

As the psuedo-values are constructed using a $U-$ statistic, Tukey(1958) conjectured that the psuedo-values may be treated as though they are independent.

Further, Shi(1984) showed that $\widehat{V}_k$ are asymptomatically independent under some mild conditions. Therefore, the jackknife estimator of θ_p is a sample average of approximately independent random variables $\widehat{V}_k$. Since Owen's empirical likelihood is easy to apply for the sample mean this motivates us to apply it to the psuedo-values $\widehat{V}_i's$.

Let the probability vector $\mathbf{p} = (p_1, p_2, \ldots, p_n)$ be such that $\sum_{i=1}^{n} p_1 = 1$ and $P_i \geq 0$ for all $1 \leq i \leq n$. Let $G_{\mathbf{p}}(x) = \sum_{i=1}^{n} p_i I(\widehat{V}_i \leq x)$. Consider the mean functional $\theta(G_{\mathbf{p}}) = \sum_{i=1}^{n} p_i \widehat{V}_i$ and let $\theta_{\mathbf{p}} = \sum_{i=1}^{n} E(\widehat{V}_i)$.

Then the empirical likelihood evaluated at θ is given by

$$L(\theta_p) = max\{\prod_{i=1}^{n} p_i : \sum_{i=1}^{n} p_i = 1, \theta(G_{\mathbf{p}}) = \theta_{\mathbf{p}}\} \tag{5}$$

So we define the jackknife ratio at θ by

$$R(\theta_p) = \frac{L(\theta_p)}{n^{-n}} = max\{\prod_{i=1}^{n}(np_i) : \sum_{i=1}^{n} p_i = 1, \theta(G_{\mathbf{p}}) = \theta_{\mathbf{p}}\}$$

Using Lagrange multipliers,when

$$min_{1\leq i\leq n}\hat{V}_i < \theta_{\mathbf{p}} < max_{1\leq i\leq n}\widehat{V}_i \tag{6}$$

we have

$$p_i = \frac{1}{n}\frac{1}{1+\lambda(\widehat{V}_i - \theta_{\mathbf{p}})} \tag{7}$$

where λ satisfies

$$f(\lambda) = \frac{1}{n}\sum_{i=1}^{n}\frac{\widehat{V}_i - \theta_{\mathbf{p}}}{1+\lambda(\widehat{V}_i - \theta_{\mathbf{p}})} = 0 \tag{8}$$

After plugging in the p_i's back into Equation (6) and taking the logarithm of $R(\theta_p)$ we get the nonparametric jackknife empirical loglikelihood ratio

$$logR(\theta_p) = -\sum_{i=1}^{n} log[1 + \lambda(\widehat{V}_i - \theta_{\mathbf{p}})] \tag{9}$$

It remains to check whether Wilk's theorem still holds here that is:

$$-2logR(\theta_p) \rightarrow \chi_1^2 \tag{10}$$

from which we can construct an approximate $(1-\alpha)$ level confidence interval for θ_p.

Using Theorem 2, we obtain the JEL based confidence interval for θ_p at $100(1-\alpha)\%$ as follows:

$$CI_p = \{\theta_p | -2l(\theta_p) \leq \chi^2_{1,1-\alpha}\} \tag{11}$$

where, $\chi^2_{1,1-\alpha}$ is the $(1-\alpha)$-th percentile point of the chi square distribution with one degree of freedom. The performance of these is verified in the following sections through a simulation study and real data.

2.1.3 Coverage probability

The coverage probability represents the probability that the true parameter value falls within the constructed confidence interval. The coverage error is defined as the discrepancy between the actual coverage probability and the nominal value. Confidence intervals with low coverage errors are preferred.

3 Simulation study

In this section, we present results from simulation studies to evaluate the finite sample performance of the JEL estimator for tail conditional variance, $\widehat{\theta}_p$ obtained in Equation (3). We simulated 500 times for sample sizes $n =$

50, 100, 200, 500 and evaluate the performance of the confidence intervals in terms of coverage probabilities as presented in Equation (11). The simulation is carried out using R software.

We simulate observations from the Standard Normal distribution, $2-$ parameter Weibull distribution, Gamma distribution and Lognormal distribution. We present therein results for 95% confidence intervals for $\widehat{\theta}_p$ coverage probability (CP) of the confidence intervals. The simulation results of each distribution mentioned above are given in Tables 1-4.

Table 1: Results for 95% JEL-based CI for TCV: standard normal distribution

n	Coverage Probability
50	0.916
100	0.93
200	0.944
500	0.952

Table 2: Results for 95% JEL based CI for TCV: 2-parameter Weibull distribution (shape=1, scale = 2)

n	Coverage Probability
50	0.9
100	0.872
200	0.888
500	0.922

Table 3: Results for 95% JEL based CI for TCV: Gamma distribution (shape=2, scale = 3)

n	Coverage Probability
50	0.854
100	0.866
200	0.916
500	0.936

Table 4: Results for 95% JEL based CI for TCV: Lognormal distribution (mean = 50, standard deviation = 10)

n	Coverage Probability
50	0.89
100	0.936
200	0.956
500	0.966

From Tables 1-4, we observe that as the sample size increases, the coverage probabilities tend to the nominal value.

Further Tables 1-4, we can see that the confidence intervals calculated using the JEL method achieves coverage probability closer to 95%. Simulation results also show that the JEL based confidence intervals for TCV at the $p-$ quantile have well-controlled coverage probability.

4 Application of JEL based CI for TCV to Mean-Variance Portfolio theory

In this section, we implement the JEL based confidence intervals for TCV within the framework of asset allocation in investments. We illustrate the proposed measure using the classical mean-variance portfolio analysis by incorporating tail risk using TCV, and estimate it with nonparametric confidence regions via JEL. This provides a robust inference framework under non-Gaussian asset returns.

Consider the investor problem of determining the proportions to invest in each of n available assets, which may include a risk-free asset. Suppose that the rate-of-return, in a single period, for these assets is a random vector represented by $\boldsymbol{R^T} = (R_1, R_2, \ldots, R_n)$. Now if w_i denotes the proportion of wealth invested in asset i, then the portfolio rate of return can be expressed as $R_p = \sum_{i=1}^{n} w_i R_i$. To construct the (Markowitz, 1952) mean-variance portfolio, one would solve the following optimization problem:

$$min_{w_1,w_2,\ldots,w_n}\ Var(R_p); \sum w_i = 1 \tag{12}$$

subject to: (i) a target rate of return, say μ_T, that is, $E(R_p) = \mu_T$, and (ii) no negative holdings, that is, $w_i \geq 0$. Instead of minimizing the variance which is a measure of the portfolio risk, one can minimize the tail variance of the portfolio. Hence, when considering tail variance, the conditioning must be on the downside risk.

4.1 Mean-variance portfolio formulation

The mean-variance portfolio can be formulated as follows: Given m assets and n observations, let $R_i \in \boldsymbol{R^m}$ be the return vector at time i, $\mu = E[R]$ and $\sum = var[R]$. Hence, portfolio return $r_p = w^T R$, where $w \in \boldsymbol{R^m}$ is the weight, mean portfolio return $\mu_p = w^T \mu$ and variance of the portfolio return is $\sigma_p^2 = w^T \sum w$. The tail conditional variance of portfolio returns below the VaR threshold at level α is

$$TCV_\alpha(w) = Var[w^T R | w^T R \leq VaR_\alpha] \tag{13}$$

4.2 Estimation of $\widehat{TCV}_\alpha$

Given the observed set of portfolio returns $\{r_{p1}, r_{p2}, \ldots, r_{pn}\}$, the empirical VaR at level α is

$$\hat{q}_\alpha = Quantile_\alpha(\{r_{pi}\}) \tag{14}$$

The select observations in the left tail are denoted as $\tau_\alpha = \{r_{pi} | r_{pi} \leq \hat{q}_\alpha\}$, the sample $\widehat{TCV}_\alpha$ is computed as:

$$\widehat{TCV}_\alpha = \frac{1}{|\tau_\alpha|} \sum_{r_{pi} \in \tau_\alpha} (r_{pi} - \bar{r}\tau_\alpha)^2 \tag{15}$$

4.3 Estimation of JEL based confidence interval for $\widehat{TCV}_\alpha$

For each observation $i = 1, 2, \ldots, n$, leave out r_{pi}, compute $\widehat{TCV}_\alpha(-i)$ using remaining $(n-1)$ returns. The jackknife psuedo values $\widehat{TCV}_\alpha(-i)$ are stored as $\widehat{\theta(i)}$, $i = 1, 2, \ldots, n$.

The empirical likelihood is constructed similar to the methodology given in Equations (5) to (10) and confidence intervals for $\widehat{TCV}_\alpha$ such that confidence bounds for the tail risk of an optimized portfolio are calculated by using JEL to solve for a candidate weight vector in the mean-variance optimization objective function: $min_w\ TCV_\alpha\ (w)\ s.t.\ w^T\mu = \mu_0$

4.4 Empirical illustration

The proposed measure is illustrated using financial time series and the analysis is carried out using R software. Consider vector of stock ticker symbols for Apple, Microsoft, and Google. We use historical stock data for the given symbols from Yahoo Finance for the specified date range (from Jan 1, 2022 to Dec 31, 2024). The daily discrete returns for each stock are computed to account for percentage change from one day to the next and missing values are checked for, typically from the first row due to return calculation. The average daily return for each stock is calculated and combined to form a new vector of portfolio returns.

Now, we compute the portfolio weights w_i as follows: we generates random, long-only portfolio weights, that are non-negative and the sum is equal to 1. This is in line with the constraints given in Equation (12). For each portfolio, the expected return is computed. The variance of quantile level for the 5% left tail $\widehat{TCV}_\alpha$ is computed using Equation (15). The Jackknife pseudo-values for each observation in the full-sample portfolio returns are computed by leaving out the $i-$th observation. The JEL based confidence interval of $\widehat{TCV}_{0.95}$ for the portfolio returns is computed. This process is repeated for 1000 portfolios. We a plot of the efficient frontier based on $\widehat{TCV}_\alpha$ and expected return r_p, with JEL confidence intervals. The plot can be interpreted as follows: X-axis represents $\widehat{TCV}_\alpha$, Y-axis represents the expected return r_p for each portfolio.

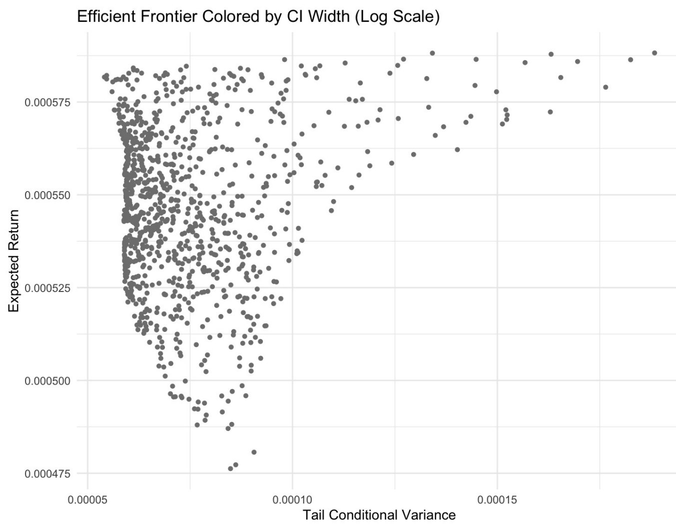

Figure 1: Plot of efficient frontier for 1000 portfolios

Since all points are rendered in the same gray color and there is no legend, it strongly suggests that the average width of the confidence interval are identical. The majority of portfolios are clustered between $\widehat{TCV}_\alpha = 0.00005$ to 0.00010, with expected returns around 0.00052 to 0.00056. The frontier has a convex-like shape on the lower end, widening in dispersion as $\widehat{TCV}_\alpha$ increases — typical of risk-return tradeoffs. The efficient frontier appears in a typical shape: low-risk weighted portfolios on the left, that is, portfolios with lower $\widehat{TCV}_\alpha(w)$ and higher-risk weighted portfolios towards the top. The clustering of points on the left suggests many portfolios share a similar low risk profile, but differ slightly in return.

5 Concluding remarks

The existing literature highlights a growing recognition of the limitations of classical mean-variance portfolio theory in capturing tail risks, particularly in volatile and non-Gaussian financial environments. Tail-based risk measures, such as CVaR and TCV, provide a more nuanced view of downside risk that is directly aligned with investor concerns.

The integration of nonparametric inference techniques—specifically empirical likelihood and jackknife resampling—has enabled more robust estimation and uncertainty quantification of these tail risk measures. The work of Peng and Qi (2006) and Jing et al. (2009) illustrates how confidence intervals for tail indices and related risk functionals can be obtained without strong distributional assumptions. This is particularly relevant in financial settings, where extreme value behavior and limited tail data present significant challenges.

Furthermore, recent contributions such as Happersberger (2020) emphasize the practical relevance of tail-focused portfolio construction and underscore the need for models that account for both performance and estimation reliability. To the best of our knowledge, this is the first study that focuses on developing JEL based CI for TCV in the context of mean-variance portfolio analysis. Further, visualizing expected return vs. TCV (instead of variance) provides a tail-aware efficient frontier based on risk weights of portfolios.

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