

# Near-consistent robust estimations of moments for unimodal distributions

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**Descriptive statistics for parametric models currently heavily rely on the accuracy of distributional assumptions. Here, leveraging the invariant structures of unimodal distributions, a series of sophisticated yet efficient estimators, robust to both gross errors and departures from parametric assumptions, are proposed for estimating mean and central moments for common unimodal distributions. This article also illuminates the understanding of the common nature of probability distributions and the measures of them.**

orderliness | invariant | unimodal | adaptive estimation |  $U$ -statistics

The potential inconsistencies between the sample mean ( $\bar{x}$ ) and robust location estimators in distributions with finite moments have been noticed for more than two centuries (1), with numerous significant attempts made to address them. In calculating a robust location estimator, the procedure of identifying and downweighting extreme values inherently necessitates the formulation of certain distributional assumptions. Inconsistencies naturally arise when these assumptions, parametric or semiparametric, are violated. Due to the presence of infinite dimensional nuisance shape parameters, the semiparametric approach struggles to adequately address distributions with more intricate shapes. Newcomb (1886) provided the first modern approach to robust parametric estimation by developing a class of estimators that gives "less weight to the more discordant observations" (2). In 1964, Huber (3) used the minimax procedure to obtain  $M$ -estimator for the contaminated normal distribution, which has played a pre-eminent role in the later development of robust statistics. However, as previously demonstrated, under growing asymmetric departures from normality, the bias of the Huber  $M$ -estimator increases rapidly. This is a common issue in parametric robust statistics. For example, He and Fung (1999) constructed (4) a robust  $M$ -estimator for the two-parameter Weibull distribution, from which all moments can be calculated. Nonetheless, it is inadequate for other parametric distributions, e.g., the gamma, Perato, lognormal, and the generalized Gaussian distributions (SI Dataset S1). Another interesting approach is based on  $L$ -estimators, such as percentile estimators. For examples of percentile estimators for the Weibull distribution, the reader is referred to the works of Menon (1963) (5), Dubey (1967) (6), Marks (2005) (7), and Boudt, Caliskan, and Croux (2011) (8). At the outset of the study of percentile estimators, it was known that they arithmetically utilize the invariant structures of probability distributions (5, 6). Maybe such estimators can be named as  $I$ -statistics. Formally, an estimator is classified as an  $I$ -statistic if it asymptotically satisfies  $I(LE_1, \dots, LE_l) = (\theta_1, \dots, \theta_q)$  for the distribution it is consistent, where LEs are calculated with the use of  $LU$ -statistics (defined in Subsection ??),  $I$  is defined using arithmetic operations and constants but may also incorporate transcendental functions and quantile functions, and  $\theta$ s are the population parameters it estimates. A subclass of  $I$ -statistics,

arithmetic  $I$ -statistics, is defined as LEs are  $LU$ -statistics,  $I$  is solely defined using arithmetic operations and constants. Since some percentile estimators use the logarithmic function to transform all random variables before computing the  $L$ -estimators, a percentile estimator might not always be an arithmetic  $I$ -statistic (6). In this article, two subclasses of  $I$ -statistics are introduced, arithmetic  $I$ -statistics and quantile  $I$ -statistics. Examples of quantile  $I$ -statistics will be discussed later. Based on  $LU$ -statistics,  $I$ -statistics are naturally robust. Compared to probability density functions (pdfs) and cumulative distribution functions (cdfs), the quantile functions of many parametric distributions are more elegant. Since the expectation of an  $L$ -estimator can be expressed as an integral of the quantile function,  $I$ -statistics are often analytically obtainable. However, it is observed that even when the sample follows a gamma distribution, which belongs to the same larger family as the Weibull model, the generalized gamma distribution, a misassumption can still lead to substantial biases in Marks percentile estimator (7), rendering the approach ill-suited (SI Dataset S1).

Most robust location estimators commonly used are symmetric owing to the prevalence of symmetric distributions. An asymmetric  $\gamma$ -weighted  $L$ -statistic can achieve consistency for any  $\gamma$ -symmetric distribution, if  $\gamma \neq 1$ . However, it is tailored more towards certain specific distributions rather than a broad spectrum of common ones. Shifting from semiparametrics to parametrics, consider an estimator with a non-sample-dependent breakdown point (defined in Subsection ??) that is consistent simultaneously for both a semiparametric class of distributions and a distinct parametric distribution, such a robust estimator is named with the prefix 'invariant' followed by the population parameter it is consistent with. Here, the recombined mean is defined as

$$rm_{d,\epsilon,\gamma,n,WL} := \lim_{c \rightarrow \infty} \left( \frac{(WL_{\epsilon,\gamma,n} + c)^{d+1}}{(\gamma m_n + c)^d} - c \right),$$

where  $d$  is the key factor for bias correction,  $\gamma m_n$  is the sample  $\gamma$ -median,  $WL_{\epsilon,\gamma,n}$  is the weighted  $L$ -statistic. It is assumed

## Significance Statement

Bias, variance, and contamination are the three main errors in statistics. Consistent robust estimation is unattainable without parametric assumptions. In this article, invariant moments are proposed as a means of achieving near-consistent and robust estimations of moments, even in scenarios where moderate violations of distributional assumptions occur, while the variances are sometimes smaller than those of the sample moments.

T.L. designed research, performed research, analyzed data, and wrote the paper.

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in this article that in the subscript of an invariant moment, if  $\gamma$  is omitted,  $\gamma = 1$  is assumed, if  $n$  is omitted, only the asymptotic behavior is considered. The subsequent theorem shows the significance of this arithmetic  $I$ -statistic.

**Theorem .1.** *Assuming finite second moments,  $rm_{d=\frac{\mu-WL_{\epsilon,\gamma}}{WL_{\epsilon,\gamma}-Q(\frac{\gamma}{1+\gamma})},\epsilon,\gamma,WL}$  is a consistent mean estimator for a location-scale distribution and any  $\gamma$ -symmetric distributions, where  $\mu$ ,  $WL_{\epsilon,\gamma}$ , and  $Q(\frac{\gamma}{1+\gamma})$  are location parameters from that location-scale distribution.*

*Proof.* Finding  $d$  that make  $rm_{d,\epsilon,\gamma,WL}$  a consistent mean estimator is equivalent to finding the solution of  $rm_{d,\epsilon,\gamma,WL} = \mu$ . First consider the location-scale distribution. Since  $rm_{d,\epsilon,\gamma,WL} = \lim_{c \rightarrow \infty} \left( \frac{(\frac{\mu-WL_{\epsilon,\gamma}}{\gamma m+c})^{d+1}}{(\gamma m+c)^d} - c \right) = (d+1) WL_{\epsilon,\gamma} - dQ(\frac{\gamma}{1+\gamma}) = \mu$ . So,  $d = \frac{\mu-WL_{\epsilon,\gamma}}{WL_{\epsilon,\gamma}-Q(\frac{\gamma}{1+\gamma})}$ . Previously, it was established that any  $WL_{\epsilon,\gamma}$  can be expressed as  $\lambda WL_0(\epsilon, \gamma) + \mu$  for a location-scale distribution parameterized by a location parameter  $\mu$  and a scale parameter  $\lambda$ , where  $WL_0(\epsilon, \gamma)$  denote the weighted  $L$ -statistic of a standard distribution without any shifts or scaling. The simultaneous cancellation of  $\mu$  and  $\lambda$  in  $\frac{(\lambda\mu_0+\mu)-(\lambda WL_0(\epsilon,\gamma)+\mu)}{(\lambda WL_0(\epsilon,\gamma)+\mu)-(\lambda\gamma m_0+\mu)}$  assures that the  $d$  in  $rm$  is always a constant for a location-scale distribution. The proof of the second assertion follows directly from the coincidence property. According to Theorem 20 in the previous article, for any  $\gamma$ -symmetric distribution with a finite second moment,  $WL_{\epsilon,\gamma} = Q(\frac{\gamma}{1+\gamma}) = \mu$ . Then  $rm_{d,\epsilon,\gamma,WL} = \lim_{c \rightarrow \infty} \left( \frac{(\mu+c)^{d+1}}{(\mu+c)^d} - c \right) = \mu$ . This completes the demonstration.  $\square$

For example, the Pareto distribution has a quantile function  $Q_{Par}(p) = x_m(1-p)^{-\frac{1}{\alpha}}$ , when  $\alpha \rightarrow \infty$ , where  $x_m$  is the minimum possible value that a random variable following the Pareto distribution can take, serving a scale parameter. The mean of the Pareto distribution is given by  $\frac{\alpha x_m}{\alpha-1}$ . As  $WL_{\epsilon,\gamma}$  can be expressed as an integral of the quantile function, the  $\gamma$ -median is also a quantile, one can replace the  $WL_{\epsilon,\gamma}$  and  $\gamma m$  in the  $d$  value with two arbitrary quantiles  $Q_{Par}(p_1)$  and  $Q_{Par}(p_2)$ . For the Pareto distribution,  $d_{Per} = \frac{\mu_{Per}-Q_{Par}(p_1)}{Q_{Par}(p_1)-Q_{Par}(p_2)} = \frac{\frac{\alpha x_m}{\alpha-1}-x_m(1-p_1)^{-\frac{1}{\alpha}}}{x_m(1-p_1)^{-\frac{1}{\alpha}}-x_m(1-p_2)^{-\frac{1}{\alpha}}}$ .  $x_m$  can be canceled out. Intriguingly, the quantile function of exponential distribution is  $Q_{exp}(p) = \ln(\frac{1}{1-p})\lambda$ ,  $\lambda \geq 0$ .  $\mu_{exp} = \lambda$ . Then,  $d_{exp} = \frac{\mu_{exp}-Q_{exp}(p_1)}{Q_{exp}(p_1)-Q_{exp}(p_2)} = \frac{\lambda-\ln(\frac{1}{1-p_1})\lambda}{\ln(\frac{1}{1-p_1})\lambda-\ln(\frac{1}{1-p_2})\lambda} = \frac{\lambda-\ln(\frac{1}{1-p_1})}{\ln(\frac{1}{1-p_1})-\ln(\frac{1}{1-p_2})}$ . Since  $\lim_{\alpha \rightarrow \infty} \frac{\frac{\alpha}{\alpha-1}-(1-p_1)^{-1/\alpha}}{(1-p_1)^{-1/\alpha}-(1-p_2)^{-1/\alpha}} = \frac{\ln(1-p_1)+1}{\ln(1-p_1)-\ln(1-p_2)}$ , the  $d$  value for the Pareto distribution approaches that of the exponential distribution, as  $\alpha \rightarrow \infty$ , regardless of the type of weighted  $L$ -statistic used. That means, for the Weibull, gamma, Pareto, lognormal and generalized Gaussian distribution,  $rm_{d=\frac{\mu-WL_{\epsilon,\gamma}}{WL_{\epsilon,\gamma}-Q_{exp}(\frac{\gamma}{1+\gamma})},\epsilon,\gamma,WL}$  is consistent for at least one particular case, where  $\mu$ ,  $WL_{\epsilon,\gamma}$ , and  $Q_{exp}(\frac{\gamma}{1+\gamma})$  are location parameters from an exponential distribution. When  $\gamma = 1$ ,  $\mu = \lambda$ ,  $m = Q(\frac{1}{2}) = \ln 2\lambda$ ,  $BM_{\nu=3,\epsilon=\frac{1}{24}} = \lambda \left( 1 + \ln \left( \frac{26068394603446272 \sqrt[6]{\frac{\gamma}{247}} \sqrt[3]{11}}{391^{5/6} 101898752449325 \sqrt{5}} \right) \right)$ , the detailed formula is given in the SI Text. So,  $d =$

$$\frac{\mu-BM_{\nu=3,\epsilon=\frac{1}{24}}}{BM_{\nu=3,\epsilon=\frac{1}{24}}-m} = \frac{\lambda-\lambda \left( 1 + \ln \left( \frac{26068394603446272 \sqrt[6]{\frac{\gamma}{247}} \sqrt[3]{11}}{391^{5/6} 101898752449325 \sqrt{5}} \right) \right)}{\lambda \left( 1 + \ln \left( \frac{26068394603446272 \sqrt[6]{\frac{\gamma}{247}} \sqrt[3]{11}}{391^{5/6} 101898752449325 \sqrt{5}} \right) \right) - \ln 2\lambda} = \frac{\ln \left( \frac{26068394603446272 \sqrt[6]{\frac{\gamma}{247}} \sqrt[3]{11}}{391^{5/6} 101898752449325 \sqrt{5}} \right)}{1 - \ln(2) + \ln \left( \frac{26068394603446272 \sqrt[6]{\frac{\gamma}{247}} \sqrt[3]{11}}{391^{5/6} 101898752449325 \sqrt{5}} \right)} \approx 0.103. \quad \text{The biases}$$

of  $rm_{d \approx 0.103, \nu=3, \epsilon=\frac{1}{24}, BM}$  for distributions with skewness between those of the exponential and symmetric distributions are tiny (SI Dataset S1).  $rm_{d \approx 0.103, \nu=3, \epsilon=\frac{1}{24}, BM}$  exhibits excellent performance for all these common unimodal distributions (SI Dataset S1).

Besides introducing the concept of invariant mean, the purpose of this paper is to demonstrate that, in light of previous works, the estimation of central moments can be transformed into a location estimation problem by using  $U$ -statistics, the central moment kernel distributions possess desirable properties, and a series of sophisticated yet efficient robust estimators can be constructed whose biases are typically smaller than the variances (as seen in Table ?? for  $n = 4096$ ) for unimodal distributions.

**A. Invariant mean.** The recombined mean is an arithmetic  $I$ -statistic. Although if  $\gamma = 1$ , it can be consistent for both a symmetric distribution and a skewed distribution, its performance tends to decrease when the skewness surpasses certain values (SI Dataset S1). Consider another kind of  $I$ -statistics. An estimator is classified as a quantile  $I$ -statistic if its LEs are percentiles of a distribution obtained by plugging  $LU$ -statistics into a cumulative distribution function, and if  $I$  is defined with arithmetic operations, constants and quantile functions. Similarly, the quantile mean can be defined as  $qm_{d,\epsilon,\gamma,n,WL} :=$

$$\begin{cases} \hat{Q}_n \left( \left( \hat{F}_n(WL) - \frac{\gamma}{1+\gamma} \right) d + \hat{F}_n(WL) \right) & \hat{F}_n(WL) \geq \frac{\gamma}{1+\gamma} \\ \hat{Q}_n \left( \hat{F}_n(WL) - \left( \frac{\gamma}{1+\gamma} - \hat{F}_n(WL) \right) d \right) & \hat{F}_n(WL) < \frac{\gamma}{1+\gamma} \end{cases}$$

where  $WL$  is  $WL_{\epsilon,\gamma,n}$ ,  $\hat{F}_n(x)$  is the empirical cumulative distribution function of the sample,  $\hat{Q}_n$  is the sample quantile function. Moreover, in extreme right-skewed heavy-tailed distributions, if the calculated percentile exceeds  $1 - \epsilon$ , it will be adjusted to  $1 - \epsilon$ , which is the same for a left-skewed distribution, if the obtained percentile is smaller than  $\gamma\epsilon$ . Without loss of generality, in the following discussion, only the case where  $\hat{F}_n(WL_{\epsilon,\gamma,n}) \geq \frac{\gamma}{1+\gamma}$  is considered. A widely used method for calculating the sample quantile function involves employing linear interpolation of modes corresponding to the order statistics of the uniform distribution on the interval  $[0, 1]$ , i.e.,  $\hat{Q}_n(p) = X_{[h]} + (h - [h])(X_{[h]} - X_{[h]})$ ,  $h = (n-1)p + 1$ . To minimize the finite sample bias, here, the inverse function of  $\hat{Q}_n$  is deduced as  $\hat{F}_n(x) := \frac{1}{n-1} \left( cf - 1 + \frac{x - X_{cf}}{X_{cf+1} - X_{cf}} \right)$ , where  $cf = \sum_{i=1}^n \mathbf{1}_{X_i \leq x}$ ,  $\mathbf{1}_A$  is the indicator of event  $A$ . The quantile mean uses the location-scale invariant in a different way, as shown in the subsequent proof.

**Theorem A.1.**  $qm_{d=\frac{F(\mu)-F(WL_{\epsilon,\gamma})}{F(WL_{\epsilon,\gamma})-\frac{\gamma}{1+\gamma}},\epsilon,\gamma,WL}$  is a consistent mean estimator for a location-scale distribution and any  $\gamma$ -symmetric distributions provided that the second moments are finite and  $F(\mu)$ ,  $F(WL_{\epsilon,\gamma})$  and  $\frac{\gamma}{1+\gamma}$  are all within the range of  $[\gamma\epsilon, 1 - \epsilon]$ , where  $\mu$  and  $WL_{\epsilon,\gamma}$  are location parameters from that location-scale distribution.

*Proof.* When  $F(WL_{\epsilon,\gamma}) \geq \frac{\gamma}{1+\gamma}$ , the solution of

167  $(F(WL_{\epsilon,\gamma}) - \frac{\gamma}{1+\gamma})d + F(WL_{\epsilon,\gamma}) = F(\mu)$  is  $d =$   
168  $\frac{F(\mu) - F(WL_{\epsilon,\gamma})}{F(WL_{\epsilon,\gamma}) - \frac{\gamma}{1+\gamma}}$ . The case where  $F(WL_{\epsilon,\gamma,n}) < \frac{\gamma}{1+\gamma}$  is the  
169 same. Since the definitions of the location and scale parameters are such that they must satisfy  $F(x; \lambda, \mu) = F(\frac{x-\mu}{\lambda}; 1, 0)$ .  
170 By recalling  $WL = \lambda WL_0(\epsilon, \gamma) + \mu$ , it follows that the percentile of any weighted  $L$ -statistic is free of  $\lambda$  and  $\mu$ . Therefore  
171  $d$  in  $qm$  is also invariably a constant. For the  $\gamma$ -symmetric case,  $F(WL_{\epsilon,\gamma}) = F(\mu) = \frac{\gamma}{1+\gamma}$  is valid for any  $\gamma$ -symmetric  
172 distribution with a finite second moment, as the same values correspond to same percentiles. Then,  $qm_{d,\epsilon,\gamma,WL} =$   
173  $F^{-1}((F(WL_{\epsilon,\gamma}) - \frac{\gamma}{1+\gamma})d + F(\mu)) = F^{-1}(0 + F(\mu)) = \mu$ .  
174 To avoid inconsistency due to post-adjustment,  $F(\mu)$ ,  
175  $F(WL_{\epsilon,\gamma})$  and  $\frac{\gamma}{1+\gamma}$  must reside the confines of  $[\gamma\epsilon, 1 - \epsilon]$ . All  
176 results are now proven.  $\square$

181 A similar relation of  $d$  values for the Pareto distribution  
182 and the exponential distribution can be established for  
183 the quantile mean. The cdf of the Pareto distribution is  
184  $1 - (\frac{x_m}{x})^\alpha$ ,  $x \geq 0$ . Replacing the  $F(WL_{\epsilon,\gamma})$  and  $\frac{\gamma}{1+\gamma}$   
185 in the  $d$  value with two arbitrary percentiles  $p_1$  and  $p_2$ ,

$$186 \quad d_{Par} = \frac{1 - \left(\frac{x_m}{\alpha x_{m1}}\right)^\alpha - \left(1 - \left(\frac{x_m}{x_m(1-p_1)}\right)^\alpha\right)}{\left(1 - \left(\frac{x_m}{x_m(1-p_1)}\right)^\alpha\right) - \left(1 - \left(\frac{x_m}{x_m(1-p_2)}\right)^\alpha\right)} =$$

$$187 \quad \frac{1 - \left(\frac{\alpha-1}{\alpha}\right)^\alpha - p_1}{\frac{p_1 - p_2}{p_1 - p_2}}. \text{ When } \alpha \rightarrow \infty, \left(\frac{\alpha-1}{\alpha}\right)^\alpha = \frac{1}{e}, \text{ so in this case,}$$

$$188 \quad d_{Par} \text{ is identical to that of the exponential distribution, since}$$

$$189 \quad \text{the cdf of the exponential distribution is } F(x) = 1 - e^{-\lambda^{-1}x},$$

$$190 \quad d_{exp} = \frac{(1-e^{-1}) - \left(1 - e^{-\ln\left(\frac{1}{1-p_1}\right)}\right)}{\left(1 - e^{-\ln\left(\frac{1}{1-p_1}\right)}\right) - \left(1 - e^{-\ln\left(\frac{1}{1-p_2}\right)}\right)} = \frac{1 - \frac{1}{e} - p_1}{p_1 - p_2}.$$

191 Following the same logic as above, their  $d$  values are always  
192 identical, regardless of the type of weighted  $L$ -statistic used, as  
193 long as the percentiles lie within the range of  $[\gamma\epsilon, 1 - \epsilon]$ . When  
194  $\gamma = 1$ ,  $WL_{\epsilon,\gamma} = BM_{\nu=3,\epsilon}$ ,  $\epsilon = \frac{1}{24}$ ,  $d = \frac{F(\mu) - F(BM_{\nu=3,\epsilon})}{F(BM_{\nu=3,\epsilon}) - \frac{1}{2}} =$   
195  $\frac{-e^{-1} + e - \left(1 + \ln\left(\frac{26068394603446272 \sqrt[6]{\frac{7}{247}} \sqrt[3]{11}}{391^{5/6} 101898752449325 \sqrt{5}}\right)\right)}{-\left(1 + \ln\left(\frac{26068394603446272 \sqrt[6]{\frac{7}{247}} \sqrt[3]{11}}{391^{5/6} 101898752449325 \sqrt{5}}\right)\right)} =$   
196  $\frac{\frac{101898752449325 \sqrt{5} \sqrt[6]{\frac{7}{247}} 391^{5/6}}{26068394603446272 \sqrt[3]{11} e} - \frac{1}{e}}{\frac{1}{2} - \frac{101898752449325 \sqrt{5} \sqrt[6]{\frac{7}{247}} 391^{5/6}}{26068394603446272 \sqrt[3]{11} e}} \approx 0.088.$  All percentiles

197 fall within the confines of  $[\frac{1}{24}, \frac{23}{24}]$ .  $qm_{d \approx 0.088, \nu=3, \epsilon=\frac{1}{24}, BM}$   
198 works better in the fat-tail scenarios (SI Dataset S1).  
199 Theorem .1 and A.1 show that  $rm_{d \approx 0.103, \nu=3, \epsilon=\frac{1}{24}, BM}$  and  
200  $qm_{d \approx 0.088, \nu=3, \epsilon=\frac{1}{24}, BM}$  are both consistent mean estimators  
201 for any symmetric distribution and a skewed parametric  
202 distribution with finite second moments. The breakdown  
203 points of  $rm_{d \approx 0.103, \nu=3, \epsilon=\frac{1}{24}, BM}$  and  $qm_{d \approx 0.088, \nu=3, \epsilon=\frac{1}{24}, BM}$   
204 are both  $\frac{1}{24}$ . Therefore they are all invariant means.

205 To study the impact of the choice of WLs in  $rm$  and  $qm$ ,  
206 it is constructive to recall that a weighted  $L$ -statistic is a  
207 combination of order statistics. While using a less-biased  
208 weighted  $L$ -statistic can generally enhance performance (SI  
209 Dataset S1), there is a greater risk of violation in the semi-  
210 parametric framework. However, the mean- $WA_{\epsilon,\gamma}$ -median  
211 inequality is robust to slight fluctuations of the QA function  
212 of the underlying distribution when  $0 \leq \gamma \leq 1$ . Suppose the

QA function is generally decreasing in  $[0, u]$ , but increasing  
in  $[u, \frac{1}{1+\gamma}]$ , since all quantile averages with upper breakdown  
points (defined in Subsection ) from  $\epsilon$  to  $\frac{1}{1+\gamma}$  will be included  
in the computation of  $WA_{\epsilon,\gamma}$ , as long as  $\frac{1}{1+\gamma} - u \ll \frac{1}{1+\gamma} - \epsilon$ ,  
and other portions of the QA function satisfy the inequality  
constraints that define the  $\nu$ th  $\gamma$ -orderliness on which  
the  $WA_{\epsilon,\gamma}$  is based, the mean- $WA_{\epsilon,\gamma}$ -median inequality still  
holds. This is due to the violation being bounded (9) when  
 $0 \leq \gamma \leq 1$  and therefore cannot be extreme for unimodal  
distributions with finite second moments. For instance, the  
SQA function is non-monotonic when the shape parameter  
of the Weibull distribution  $\alpha > \frac{1}{1-\ln(2)} \approx 3.259$  as shown  
in the previous article, the violation of the third orderliness  
starts near this parameter as well. Yet the mean- $BM_{\nu=3, \epsilon=\frac{1}{24}}$ -  
median inequality remains valid when  $\alpha \leq 3.387$ . Another key  
factor in determining the risk of violation is the skewness of  
the distribution. Previously, it was demonstrated that in a  
family of distributions differing by a skewness-increasing trans-  
formation in van Zwet's sense, the violation of orderliness, if it  
happens, often only occurs as the distribution nears symmetry  
(10). When  $\gamma = 1$ , the over-corrections in  $rm$  and  $qm$  are  
dependent on the  $SWA_{\epsilon}$ -median difference, which can be a  
reasonable measure of skewness after standardization (11, 12),  
implying that the over-correction is often tiny with moderate  
 $d$ . This qualitative analysis suggests the general reliability of  
 $rm$  and  $qm$  based on the mean- $WA_{\epsilon,\gamma}$ -median inequality for  
unimodal distributions with finite second moments. Extending  
this rationale to other weighted  $L$ -statistics is possible,  
since the  $\gamma$ - $U$ -orderliness can also be bounded with certain  
assumptions, as discussed previously.

**Data Availability.** Data for Table ?? are given in SI Dataset S1.  
All codes have been deposited in [GitHub](#).

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1. CF Gauss, *Theoria combinationis observationum erroribus minimis obnoxiae*. (Henricus Dieterich), (1823).
2. S Newcomb, A generalized theory of the combination of observations so as to obtain the best result. *Am. journal Math.* **8**, 343–366 (1886).
3. PJ Huber, Robust estimation of a location parameter. *Ann. Math. Stat.* **35**, 73–101 (1964).
4. X He, WK Fung, Method of medians for lifetime data with weibull models. *Stat. medicine* **18**, 1993–2009 (1999).
5. M Menon, Estimation of the shape and scale parameters of the weibull distribution. *Technometrics* **5**, 175–182 (1963).
6. SD Dubey, Some percentile estimators for weibull parameters. *Technometrics* **9**, 119–129 (1967).
7. NB Marks, Estimation of weibull parameters from common percentiles. *J. applied Stat.* **32**, 17–24 (2005).
8. K Boudt, D Caliskan, C Croux, Robust explicit estimators of weibull parameters. *Metrika* **73**, 187–209 (2011).
9. C Bernard, R Kazzi, S Vanduffel, Range value-at-risk bounds for unimodal distributions under partial information. *Insur. Math. Econ.* **94**, 9–24 (2020).
10. WR van Zwet, *Convex Transformations of Random Variables: Nebst Stellingen*. (1964).
11. AL Bowley, *Elements of statistics*. (King) No. 8, (1926).
12. RA Groeneveld, G Meeden, Measuring skewness and kurtosis. *J. Royal Stat. Soc. Ser. D (The Stat.)* **33**, 391–399 (1984).