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2 **Supporting Information for**

3 **Semiparametric robust mean estimation based on the orderliness of quantile averages**

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6 **This PDF file includes:**

- 7 Supporting text
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11 **Other supporting materials for this manuscript include the following:**

- 12 Dataset S1

Supporting Information Text

Methods

The asymptotic biases of all robust location estimators proposed in this article for the Weibull, gamma, Pareto, and lognormal distributions were computed within the specified range of kurtosis and standardized by the standard deviations of the respective distributions. For the Weibull, gamma, and lognormal distributions, the kurtosis range is from 3 to 15 (there are two shape parameter solutions for the Weibull distribution, the lower one is used here). For the Pareto distribution, the range is from 9 to 21.

The asymptotic results were approximated by a quasi-Monte Carlo study (1, 2) based on generating a large quasi-random sample with sample size 1.8 million for corresponding distributions and quasi-subsampling the sample 1.8k million times (3) to approximate the distributions of the kernels of the weighted Hodges-Lehmann mean. The accuracies were checked by comparing the results to the asymptotic values for the exponential distribution, showing that the errors were all smaller than 0.001σ .

The standard errors of all these estimators for the generalized Gaussian distribution, whose kurtosis range is from 3 to 15, were computed by approximating the sampling distribution with 1000 pseudorandom samples with sample size $n = 5400$. Common random numbers were used for better comparison.

Orderliness and weighted average inequality

Unlike the mean-median-mode inequality, whose necessary and sufficient condition is often hard to compute. The following result highlights another advantage of trimming inequality.

Theorem 0.1. *A necessary and sufficient condition of the γ -trimming inequality is the monotonic behavior of the bias of trimmed mean as a function of the breakdown point ϵ .*

Proof. Just considering the right-skewed distributions without loss of generality, from the definition of γ -trimming inequality, since $\forall \epsilon_1 \leq \epsilon_2 \leq \frac{1}{1+\gamma}$, $\text{TM}_{\epsilon_1, \gamma} \geq \text{TM}_{\epsilon_2, \gamma}$, therefore

$$\frac{\text{TM}_{\epsilon_1, \gamma} - \mu}{\sigma} \geq \frac{\text{TM}_{\epsilon_2, \gamma} - \mu}{\sigma} \iff B_{\text{TM}_{\epsilon_1, \gamma}} \geq B_{\text{TM}_{\epsilon_2, \gamma}} \iff B_{\text{TM}}(\epsilon_1, \gamma) \geq B_{\text{TM}}(\epsilon_2, \gamma),$$

which implies the monotonicity of $B_{\text{TM}}(\epsilon, \gamma)$ with respect to ϵ . \square

The bias function is free of scale parameter, so the derivatives are much easier to compute. A useful sufficient condition is the monotonicity of symmetric quantile average with respect to ϵ .

Theorem 0.2. *A sufficient condition of the trimming inequality for a right-skewed distribution is the monotonicity of the symmetric quantile average with respect to the breakdown point ϵ .*

Proof. The trimming inequality is equivalent to, $\forall 0 < \epsilon < \frac{1}{2}$, $\frac{1}{1-2\epsilon+2\delta} \int_{\epsilon-\delta}^{1-\epsilon+\delta} Q(u) du \geq \frac{1}{1-2\epsilon} \int_{\epsilon}^{1-\epsilon} Q(u) du$, where δ is an infinitesimal quantity.

$$\begin{aligned} & \text{Then, by deducing } \frac{1}{1-2\epsilon+2\delta} \int_{\epsilon-\delta}^{1-\epsilon+\delta} Q(u) du = \frac{1}{\frac{1}{2}-\epsilon+\delta} \int_{\frac{1}{2}-\epsilon+\delta}^{\frac{1}{2}} \text{SQA}(u) du = \lim_{n \rightarrow \infty} \left(\frac{1}{(\frac{1}{2}n-n\epsilon+1)} \sum_{i=n\epsilon-1}^{\frac{1}{2}n} \frac{X_i+X_{n-i}}{2} \right) \\ & > \lim_{n \rightarrow \infty} \left(\frac{1}{(\frac{1}{2}n-n\epsilon+1)} \left(\left(\sum_{i=n\epsilon}^{\frac{1}{2}n} \frac{X_i+X_{n-i}}{2} \right) + \frac{X_{n\epsilon}+X_{n-n\epsilon}}{2} \right) \right) \\ & = \lim_{n \rightarrow \infty} \left(\frac{1}{(\frac{1}{2}n-n\epsilon)} \left(\frac{(\frac{1}{2}n-n\epsilon)}{(\frac{1}{2}n-n\epsilon+1)} \left(\sum_{i=n\epsilon+1}^{\frac{1}{2}n} \frac{X_i+X_{n-i}}{2} \right) + \frac{2(\frac{1}{2}n-n\epsilon)}{(\frac{1}{2}n-n\epsilon+1)} \frac{X_{n\epsilon}+X_{n-n\epsilon}}{2} \right) \right) \\ & = \lim_{n \rightarrow \infty} \left(\frac{1}{(\frac{1}{2}n-n\epsilon)} \left(\frac{(\frac{1}{2}n-n\epsilon)}{(\frac{1}{2}n-n\epsilon+1)} \left(\sum_{i=n\epsilon+1}^{\frac{1}{2}n} \frac{X_i+X_{n-i}}{2} \right) + \frac{X_{n\epsilon}+X_{n-n\epsilon}}{2} + \frac{(\frac{1}{2}n-n\epsilon-1)}{(\frac{1}{2}n-n\epsilon+1)} \frac{X_{n\epsilon}+X_{n-n\epsilon}}{2} \right) \right) \\ & > \lim_{n \rightarrow \infty} \left(\frac{1}{\frac{1}{2}n-n\epsilon} \left(\frac{\frac{1}{2}n-n\epsilon}{\frac{1}{2}n-n\epsilon+1} \sum_{i=n\epsilon+1}^{\frac{1}{2}n} \frac{X_i+X_{n-i}}{2} + \frac{X_{n\epsilon}+X_{n-n\epsilon}}{2} + \frac{1}{\frac{1}{2}n-n\epsilon+1} \left(\frac{X_{n\epsilon+1}+X_{n-n\epsilon-1}}{2} + \dots + \frac{X_{\frac{1}{2}n}+X_{\frac{1}{2}n}}{2} \right) \right) \right) \\ & = \lim_{n \rightarrow \infty} \left(\frac{1}{(\frac{1}{2}n-n\epsilon)} \left(\left(\sum_{i=n\epsilon}^{\frac{1}{2}n} \frac{X_i+X_{n-i}}{2} \right) \right) \right) = \frac{1}{1-2\epsilon} \int_{\epsilon}^{1-\epsilon} Q(u) du, \text{ the proof is complete. } \square \end{aligned}$$

Theorem 0.3. *A necessary and sufficient condition of the γ -orderliness is the monotonic behavior of the bias of the quantile average as a function of the breakdown point ϵ .*

Proof. The proof is analogous to Theorem 0.1, just replacing the TM as QA. \square

Orderliness is more fundamental than trimming inequality; for example, orderliness also implies Winsorization inequality.

Definition 0.1 (Winsorization inequality). A distribution follows the Winsorization inequality if and only if $\forall \epsilon_1 \leq \epsilon_2 \leq \frac{1}{2}$, $\text{WM}_{\epsilon_1} \geq \text{WM}_{\epsilon_2}$, or $\forall \epsilon_1 \leq \epsilon_2 \leq \frac{1}{2}$, $\text{WM}_{\epsilon_1} \leq \text{WM}_{\epsilon_2}$.

Theorem 0.4. *A sufficient condition of the Winsorization inequality for a right-skewed distribution is the monotonicity of the symmetric quantile average function with respect to the breakdown point ϵ .*

53 *Proof.* The Winsorization inequality in Definition 0.1 is equivalent to,

54 $\forall 0 < \epsilon < \frac{1}{2}, \int_{\epsilon-\delta}^{1-\epsilon+\delta} Q(u) du + (\epsilon - \delta)(Q(\epsilon - \delta) + Q(1 - \epsilon + \delta)) \geq \int_{\epsilon}^{1-\epsilon} Q(u) du + \epsilon(Q(\epsilon) + Q(1 - \epsilon)),$ where δ is an
55 infinitesimal quantity.

56 Then, by deducing $\int_{\epsilon-\delta}^{1-\epsilon+\delta} Q(u) du + (\epsilon - \delta)(Q(\epsilon - \delta) + Q(1 - \epsilon + \delta)) = \int_{\epsilon-\delta}^{\frac{1}{2}} SQA(u) du + 2(\epsilon - \delta) SQA(\epsilon - \delta)$

57 $= \lim_{n \rightarrow \infty} \left(\frac{2}{n} \left(\sum_{i=n\epsilon-1}^{\frac{1}{2}n} \frac{X_i + X_{n-i}}{2} + (n\epsilon - 1) \left(\frac{X_{n\epsilon-1} + X_{n-n\epsilon+1}}{2} \right) \right) \right)$

58 $> \lim_{n \rightarrow \infty} \left(\frac{2}{n} \left(\sum_{i=n\epsilon}^{\frac{1}{2}n} \frac{X_i + X_{n-i}}{2} + \frac{X_{n\epsilon} + X_{n-n\epsilon}}{2} + (n\epsilon - 1) \left(\frac{X_{n\epsilon-1} + X_{n-(n\epsilon-1)}}{2} \right) \right) \right)$

59 $= \lim_{n \rightarrow \infty} \left(\frac{2}{n} \left(\sum_{i=n\epsilon}^{\frac{1}{2}n} \frac{X_i + X_{n-i}}{2} + (n\epsilon) \left(\frac{X_{n\epsilon} + X_{n-n\epsilon}}{2} \right) \right) \right)$

60 $= \int_{\epsilon}^{1-\epsilon} Q(u) du + (\epsilon)(Q(\epsilon) + Q(1 - \epsilon)),$ the proof is complete. \square

61 **Theorem 0.5.** A necessary and sufficient condition of the second orderliness is the monotonicity and convexity of the bias
62 function of the symmetric quantile average with respect to the breakdown point ϵ .

63 *Proof.* The proof is analogous to Theorem 0.1. \square

64 Then, the orderliness for parametric distributions will be discussed. For simplicity, $0 < \epsilon < \frac{1}{2}$ is assumed in the following
65 proofs unless otherwise specified.

66 **Theorem 0.6.** The Weibull distribution is ordered if the shape parameter $\alpha \leq \frac{1}{1-\ln(2)} \approx 3.259$.

Proof. The pdf of the Weibull distribution is $f(x) = \frac{\alpha e^{-\left(\frac{x}{\lambda}\right)^\alpha} \left(\frac{x}{\lambda}\right)^{\alpha-1}}{\lambda}$, $x \geq 0$, the quantile function is $F^{-1}(p) = \lambda(-\ln(1-p))^{1/\alpha}$,
67 $1 \geq p \geq 0, \alpha > 0, \lambda > 0$. Then, the standardized bias of a symmetric quantile average with a breakdown point ϵ , is

$$B_{SQA}(\epsilon, \alpha) = \frac{SQA_\epsilon - \mu}{\sigma} = \frac{\frac{1}{2}(\lambda(-\ln(1-\epsilon))^{1/\alpha} + \lambda(-\ln(\epsilon))^{1/\alpha}) - \lambda\Gamma\left(1 + \frac{1}{\alpha}\right)}{\sqrt{\lambda^2 \left(\Gamma\left(1 + \frac{2}{\alpha}\right) - \Gamma\left(1 + \frac{1}{\alpha}\right)^2 \right)}}.$$

67 $\frac{\partial B_{SQA}}{\partial \epsilon} = \frac{\frac{(-\ln(1-\epsilon))^{\frac{1}{\alpha}-1}}{\alpha-\alpha\epsilon} + \frac{(-\ln(\epsilon))^{1/\alpha}}{\alpha\epsilon \ln(\epsilon)}}{2\sqrt{\Gamma\left(\frac{\alpha+2}{\alpha}\right) - \Gamma\left(1 + \frac{1}{\alpha}\right)^2}}$. Let $g(\epsilon, \alpha) = \frac{(-\ln(1-\epsilon))^{\frac{1}{\alpha}-1}}{\alpha-\alpha\epsilon} + \frac{(-\ln(\epsilon))^{1/\alpha}}{\alpha\epsilon \ln(\epsilon)} = -(-\ln(1-\epsilon))^{\frac{1}{\alpha}}((1-\epsilon)(\ln(1-\epsilon)))^{-1} +$

68 $(-\ln(\epsilon))^{\frac{1}{\alpha}}(\epsilon \ln(\epsilon))^{-1}$. Arranging the equation $g(\epsilon, \alpha) = 0$, it can be shown that $\frac{\epsilon}{(1-\epsilon)} = \left(\frac{\ln(\epsilon)}{\ln(1-\epsilon)} \right)^{\frac{1}{\alpha}-1}$. Let $L(\epsilon) = \frac{\epsilon}{(1-\epsilon)}$,

69 $R(\epsilon, \alpha) = \left(\frac{\ln(\epsilon)}{\ln(1-\epsilon)} \right)^{\frac{1}{\alpha}-1}$, $LmR(\epsilon, \alpha) = L(\epsilon, \alpha) - R(\epsilon, \alpha)$, then $\frac{\partial LmR}{\partial \alpha} = \frac{\ln\left(\frac{\ln(\epsilon)}{\ln(1-\epsilon)}\right) \left(\frac{\ln(\epsilon)}{\ln(1-\epsilon)}\right)^{\frac{1}{\alpha}-1}}{\alpha^2}$. For $0 < \epsilon < \frac{1}{2}$, $\frac{\partial LmR}{\partial \alpha} > 0$,

70 so $LmR(\epsilon, \alpha)$ is monotonic with respect to α . When $\alpha = \frac{1}{1-\ln(2)}$, $g(\epsilon) = -\frac{1}{\epsilon(-\ln(\epsilon))^{\ln(2)}} + \frac{1}{(1-\epsilon)(-\ln(1-\epsilon))^{\ln(2)}}$. Let $h(\epsilon) =$
71 $\epsilon(-\ln(\epsilon))^{\ln(2)}$, $h'(\epsilon) = \frac{(-\ln(\epsilon))^{\ln(2)} \ln(2\epsilon)}{\ln(\epsilon)}$, for $0 < \epsilon < e^{-\ln(2)} = \frac{1}{2}$, $h'(\epsilon) > 0$. As a result, $h(\epsilon)$ is monotonic increasing,

72 $-h(1-\epsilon)$ is monotonic increasing, $h(\epsilon) - h(1-\epsilon)$ is also monotonic increasing. So, if $0 < \epsilon < \frac{1}{2}$, $h(\epsilon) - h(1-\epsilon) <$

73 $h\left(\frac{1}{2}\right) - h\left(1 - \frac{1}{2}\right) = 0$, $g(\epsilon, \alpha) < 0$. So, $\frac{\partial B_{SQA}}{\partial \epsilon} < 0$, $B_{SQA}(\epsilon, \alpha)$ is monotonic decreasing in ϵ when $\alpha \leq \frac{1}{1-\ln(2)}$. The assertion
74 follows from Theorem 0.3. \square

75 *Remark.* The Weibull distribution can be symmetric. Its skewness is $\tilde{\mu}_3 = \frac{2\Gamma\left(1 + \frac{1}{\alpha}\right)^3 - 3\Gamma\left(1 + \frac{2}{\alpha}\right)\Gamma\left(1 + \frac{1}{\alpha}\right) + \Gamma\left(1 + \frac{3}{\alpha}\right)}{\left(\Gamma\left(1 + \frac{2}{\alpha}\right) - \Gamma\left(1 + \frac{1}{\alpha}\right)^2\right)^{3/2}}$. Denote the
76 solution of $\tilde{\mu}_3 = 0$ as $\alpha_0 \approx 3.602$. The above proof implies that when α is close to α_0 , the bias function of SQA is no longer
77 monotonic.

Then, the bias function of the trimmed mean for the Weibull distribution is

$$B_{TM}(\epsilon, \alpha) = \frac{\frac{\Gamma\left(1 + \frac{1}{\alpha}, -\ln(1-\epsilon)\right) - \Gamma\left(1 + \frac{1}{\alpha}, -\ln(\epsilon)\right)}{1-2\epsilon} - \Gamma\left(1 + \frac{1}{\alpha}\right)}{\sqrt{\Gamma\left(1 + \frac{2}{\alpha}\right) - \Gamma\left(1 + \frac{1}{\alpha}\right)^2}},$$

78 Numerical solutions and the plot in Figure S1 indicate that, when $\alpha = 3.259, \epsilon = 0.1$, $\frac{\partial B_{TM}}{\partial \epsilon} \approx -0.164$, when $\epsilon = 0.4$,
79 $\frac{\partial B_{TM}}{\partial \epsilon} \approx -0.001$, when $\epsilon = 0.499$, $\frac{\partial B_{TM}}{\partial \epsilon} \approx 7.66 \times 10^{-8}$. So, the bias function of the trimmed mean can also be non-monotonic
80 when $\alpha \geq \frac{1}{1-\ln(2)}$.

81 Additionally, the second derivative of the bias function of SQA for the Weibull distribution is,

82 $\frac{\partial^2 B_{SQA}}{\partial^2 \epsilon} = \frac{-\frac{(-\ln(\epsilon))^{\frac{1}{\alpha}-1}}{\alpha^2 \epsilon^2 \ln(\epsilon)} - \frac{(-\ln(\epsilon))^{1/\alpha}}{\alpha \epsilon^2 \ln^2(\epsilon)} - \frac{(-\ln(\epsilon))^{1/\alpha}}{\alpha \epsilon^2 \ln(\epsilon)} + \frac{\left(\frac{1}{\alpha}-1\right)(-\ln(1-\epsilon))^{\frac{1}{\alpha}-2}}{(1-\epsilon)(\alpha-\alpha\epsilon)} + \frac{\alpha(-\ln(1-\epsilon))^{\frac{1}{\alpha}-1}}{(\alpha-\alpha\epsilon)^2}}{2\sqrt{\Gamma\left(\frac{\alpha+2}{\alpha}\right) - \Gamma\left(1 + \frac{1}{\alpha}\right)^2}}$. The numerical solutions show that

83 when $\alpha < 3$, $\frac{\partial^2 B_{SQA}}{\partial^2 \epsilon} > 0$, if $0 < \epsilon < \frac{1}{2}$. The flip of the signs also occurs when α is close to $\frac{1}{1-\ln(2)} \approx 3.259$. When

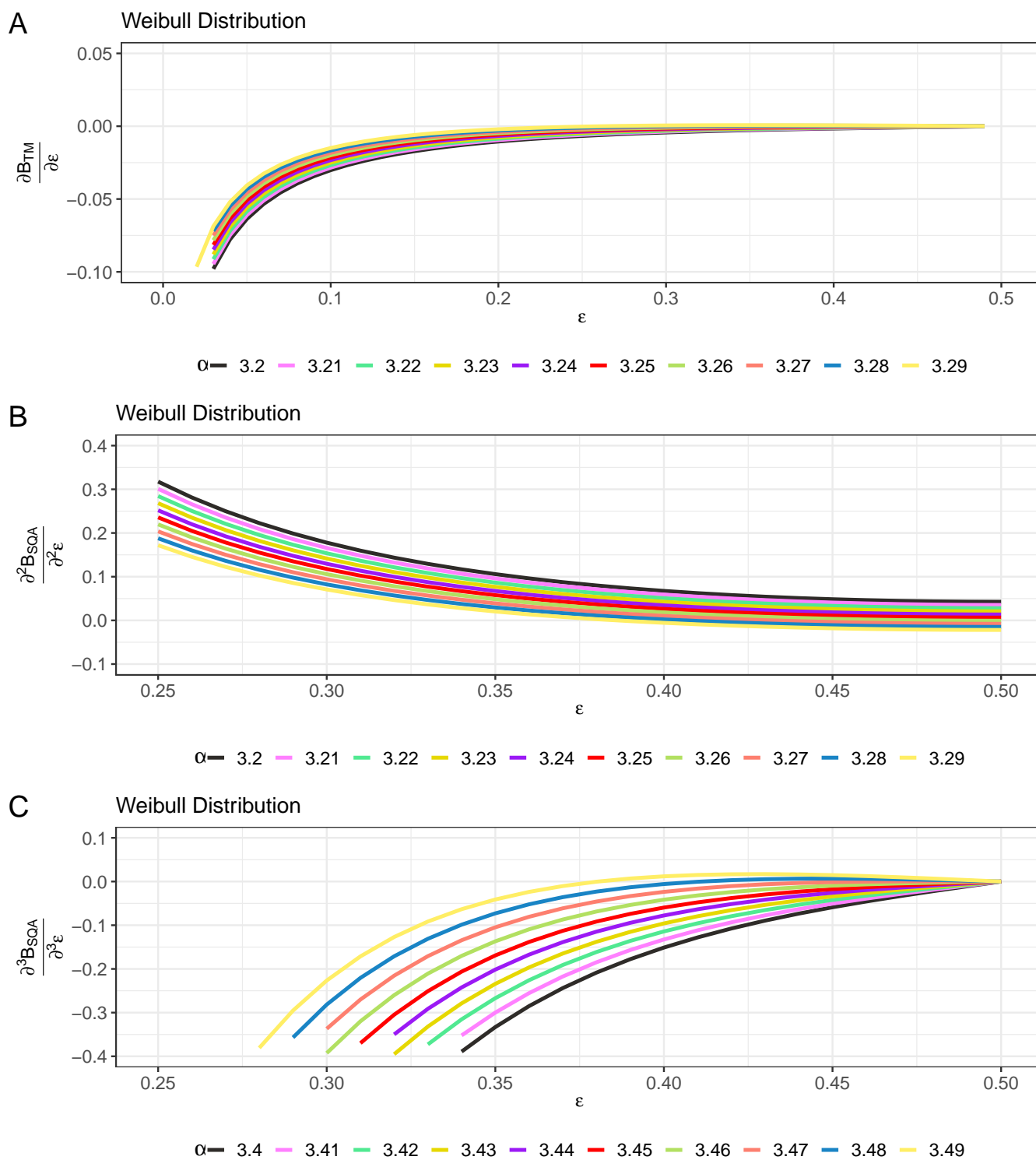


Fig. S1. A. The first derivative of the bias function of TM for the Weibull distribution as a function of the breakdown point ϵ . B. The second derivative of the bias function of SQA for the Weibull distribution as a function of the breakdown point ϵ . C. The third derivative of the bias function of SQA for the Weibull distribution as a function of the breakdown point ϵ .

84 $\alpha = \frac{1}{1-\ln(2)}, \epsilon = 0.1, \frac{\partial^2 B_{\text{SQA}}}{\partial^2 \epsilon} \approx 3.259$, when $\epsilon = 0.4, \frac{\partial^2 B_{\text{SQA}}}{\partial^2 \epsilon} \approx 0.020$, when $\epsilon = 0.5, \frac{\partial^2 B_{\text{SQA}}}{\partial^2 \epsilon} \approx -7.34 \times 10^{-16}$. A plot of
85 $\frac{\partial^2 B_{\text{SQA}}}{\partial^2 \epsilon}$ for $0.25 < \epsilon < 0.5$ is given in Figure S1.

86 Then, the third derivative of the SQA for the Weibull distribution is,

$$87 \frac{\partial^3 B_{\text{SQA}}}{\partial^3 \epsilon} = - \frac{(\alpha-1)(2\alpha-1)(\epsilon-1)^3(-\ln(\epsilon))^{\frac{1}{\alpha}-3} - 3(\alpha-1)\alpha(\epsilon-1)^3(-\ln(\epsilon))^{\frac{1}{\alpha}-2}}{2\alpha^3(\epsilon-1)^3\epsilon^3\sqrt{\Gamma(\frac{\alpha+2}{\alpha})-\Gamma(1+\frac{1}{\alpha})^2}} \\
88 - \frac{2\alpha^2\epsilon^3(-\ln(1-\epsilon))^{\frac{1}{\alpha}-1} + 2\alpha^2(\epsilon-1)^3(-\ln(\epsilon))^{\frac{1}{\alpha}-1} + (1-\alpha)(1-2\alpha)\epsilon^3(-\ln(1-\epsilon))^{\frac{1}{\alpha}-3} + 3(1-\alpha)\alpha\epsilon^3(-\ln(1-\epsilon))^{\frac{1}{\alpha}-2}}{2\alpha^3(\epsilon-1)^3\epsilon^3\sqrt{\Gamma(\frac{\alpha+2}{\alpha})-\Gamma(1+\frac{1}{\alpha})^2}}. \text{ The numerical solutions show}$$

89 that when $\alpha < 3, \frac{\partial^3 B_{\text{SQA}}}{\partial^3 \epsilon} < 0$, if $0 < \epsilon < \frac{1}{2}$. The flip of the signs occurs when $\alpha = 3.471$. When $\epsilon = 0.4, \frac{\partial^3 B_{\text{SQA}}}{\partial^3 \epsilon} \approx -0.0218$,
90 when $\epsilon = 0.499, \frac{\partial^3 B_{\text{SQA}}}{\partial^3 \epsilon} \approx 4.928 \times 10^{-5}$. A plot of $\frac{\partial^3 B_{\text{SQA}}}{\partial^3 \epsilon}$ for $0.3 < \epsilon < 0.5$ is given in Figure S1.

91 Because the kurtosis range used here for the Weibull distribution starts from 3.1, the corresponding α is 2.133, so among
92 the kurtosis range discussed here, the numerical results show that the Weibull distribution follows the first three orderlinesses.

The pdf of the gamma distribution is $f(x) = \frac{\lambda^{-\alpha} x^{\alpha-1} e^{-\frac{x}{\lambda}}}{\Gamma(\alpha)}$, $x \geq 0$, the quantile function is $Q(p) = \lambda P^{-1}(\alpha, p)$, $1 \geq p \geq 0$,
 $\alpha > 0, \lambda > 0$, P is the regularized incomplete gamma function. So, $E[X] = \int_{-\infty}^{\infty} xf(x)dx = \alpha\lambda$. Similarly, the variance is $\alpha\lambda^2$.
Then, the standardized bias of a symmetric quantile average with a breakdown point ϵ , is

$$B_{\text{SQA}}(\epsilon, \alpha) = \frac{\text{SQA}_{\epsilon} - \mu}{\sigma} = \frac{\frac{1}{2}(\lambda P^{-1}(\alpha, 1-\epsilon) + \lambda P^{-1}(\alpha, \epsilon)) - \alpha\lambda}{\sqrt{\alpha\lambda^2}}.$$

93 $\frac{\partial B_{\text{SQA}}}{\partial \epsilon} = \frac{\Gamma(\alpha)}{2\sqrt{\alpha}}(e^{P^{-1}(\alpha, \epsilon)}P^{-1}(\alpha, \epsilon)^{1-\alpha} - e^{P^{-1}(\alpha, 1-\epsilon)}P^{-1}(\alpha, 1-\epsilon)^{1-\alpha})$. It is trivial to show that when $\alpha \leq 1$, $P^{-1}(\alpha, \epsilon)$ is
94 monotonic increasing in ϵ , if $0 < \epsilon < \frac{1}{2}$. Then $\frac{\partial B_{\text{SQA}}}{\partial \epsilon} < 0$, $B_{\text{SQA}}(\epsilon, \alpha)$ is monotonic decreasing in ϵ over the interval $(0, \frac{1}{2})$.
95 However, the analytical analysis of $\alpha > 1$ is hard. Numerical results shows that the flip of signs of $\frac{\partial B_{\text{SQA}}}{\partial \epsilon}$ occurs when
96 $\alpha \approx 139.5$ (Figure S2). The second derivative of the bias function for the gamma distribution is $\frac{\partial^2 B_{\text{SQA}}}{\partial^2 \epsilon} = \frac{\Gamma(\alpha)^2}{2\sqrt{\alpha}}((1 -$
97 $\alpha)e^{2P^{-1}(\alpha, 1-\epsilon)}P^{-1}(\alpha, 1-\epsilon)^{1-2\alpha} + e^{2P^{-1}(\alpha, 1-\epsilon)}P^{-1}(\alpha, 1-\epsilon)^{2-2\alpha} + (1-\alpha)e^{2P^{-1}(\alpha, \epsilon)}P^{-1}(\alpha, \epsilon)^{1-2\alpha} + e^{2P^{-1}(\alpha, \epsilon)}P^{-1}(\alpha, \epsilon)^{2-2\alpha})$.
98 The flip of signs of $\frac{\partial^2 B_{\text{SQA}}}{\partial^2 \epsilon}$ occurs when $\alpha \approx 78$ (Figure S2). The third derivative is much more cumbersome; numerical results
99 show that the flip of signs of $\frac{\partial^3 B_{\text{SQA}}}{\partial^3 \epsilon}$ occurs when $\alpha \approx 55$ (Figure S2). Since the kurtosis range of the gamma distribution
100 starts from 3.1, the corresponding α is 60. The second point is $\alpha = 30$. Besides the first point, the numerical results show that
101 the gamma distribution follows the first three orderlinesses within the kurtosis setting here.

For the lognormal distribution, the pdf of it is $f(x) = \frac{e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma x}}$, $x \geq 0$, the quantile function is $Q(p) = e^{\mu - \sqrt{2}\sigma \text{erfc}^{-1}(2p)}$,
 $1 \geq p \geq 0, \sigma > 0, \lambda > 0$. So, $E[X] = \int_{-\infty}^{\infty} xf(x)dx = e^{\mu + \frac{\sigma^2}{2}}$. Similarly, the variance is $(e^{\sigma^2} - 1)e^{2\mu + \sigma^2}$. Then, the
standardized bias of a symmetric quantile average with a breakdown point ϵ , is

$$B_{\text{SQA}}(\epsilon, \sigma) = \frac{\frac{1}{2}\left(e^{\mu - \sqrt{2}\sigma \text{erfc}^{-1}(2\epsilon)} + e^{\mu - \sqrt{2}\sigma \text{erfc}^{-1}(2(1-\epsilon))}\right) - e^{\mu + \frac{\sigma^2}{2}}}{\sqrt{(e^{\sigma^2} - 1)e^{2\mu + \sigma^2}}}.$$

102 The first two orderlinesses for the lognormal distribution were already discussed in the Main Text, the numerical results show
103 that the third orderliness is also valid within the kurtosis setting here.

104 Bias bound

As stated in the Main Text, Bernard et al. (2020) (4) derived the bias bound of the symmetric quantile average for \mathcal{P}_U ,

$$B_{\text{SQA}}(\epsilon) = \begin{cases} \frac{1}{2} \left(\sqrt{\frac{4}{9\epsilon} - 1} + \sqrt{\frac{3\epsilon}{4-3\epsilon}} \right) & \frac{1}{6} \geq \epsilon \geq 0 \\ \frac{1}{2} \left(\sqrt{\frac{1-\epsilon}{\epsilon + \frac{1}{3}}} + \sqrt{\frac{3\epsilon}{4-3\epsilon}} \right) & \frac{1}{2} \geq \epsilon > \frac{1}{6}. \end{cases}$$

They also investigated the bias bounds of Range Value at Risk (5), which is

$$RVaR_{\alpha, \beta} = \frac{1}{\beta - \alpha} \int_{\alpha}^{\beta} VaR(u) du, 0 < \alpha < \beta < 1,$$

105 where $VaR(u) = \inf\{x \in \mathbb{R} : F_U(x) \geq u\}$. They pointed out that $VaR(u)$ is the quantile function, and it is obvious here
106 that $RVaR_{\alpha, \beta}$ is the trimmed mean. Let $\alpha = \epsilon, \beta = 1 - \gamma\epsilon$, then because of asymmetry, if setting the $\mu = 0, \sigma = 1$, the
107 upper bound $\sup_{P \in \mathcal{P}_U} (RVaR_{\alpha=\epsilon, \beta=1-\gamma\epsilon})$ and lower bound $\inf_{P \in \mathcal{P}_U} (RVaR_{\alpha=\epsilon, \beta=1-\gamma\epsilon})$ are not exactly opposite values. Also,
108 $\sup_{P \in \mathcal{P}_U} (RVaR_{\alpha=\epsilon, \beta=1-\gamma\epsilon})$ and $\inf_{P \in \mathcal{P}_U} (RVaR_{\alpha=\epsilon, \beta=1-\gamma\epsilon})$ are very complex in form. If setting $\gamma = 1$, they are opposite
109 values, i.e., the bias bound of symmetric trimmed mean is

$$110 B_{\text{STMB}}(\epsilon) = \frac{|\text{STM}_{\epsilon} - \mu|}{\sigma} = \frac{\epsilon(9\epsilon^2 + (4-3\sqrt{9\epsilon^2+4})\epsilon - \sqrt{9\epsilon^2+4}+2)}{(2\epsilon-1)\sqrt{-\frac{81\epsilon^4}{2} + 3(4\sqrt{9\epsilon^2+4}-9)\epsilon^2 + 6(\sqrt{9\epsilon^2+4}-2)\epsilon + \frac{4}{3}(\sqrt{9\epsilon^2+4}-2) + \frac{9}{2}(3\sqrt{9\epsilon^2+4}-8)\epsilon^3}}.$$

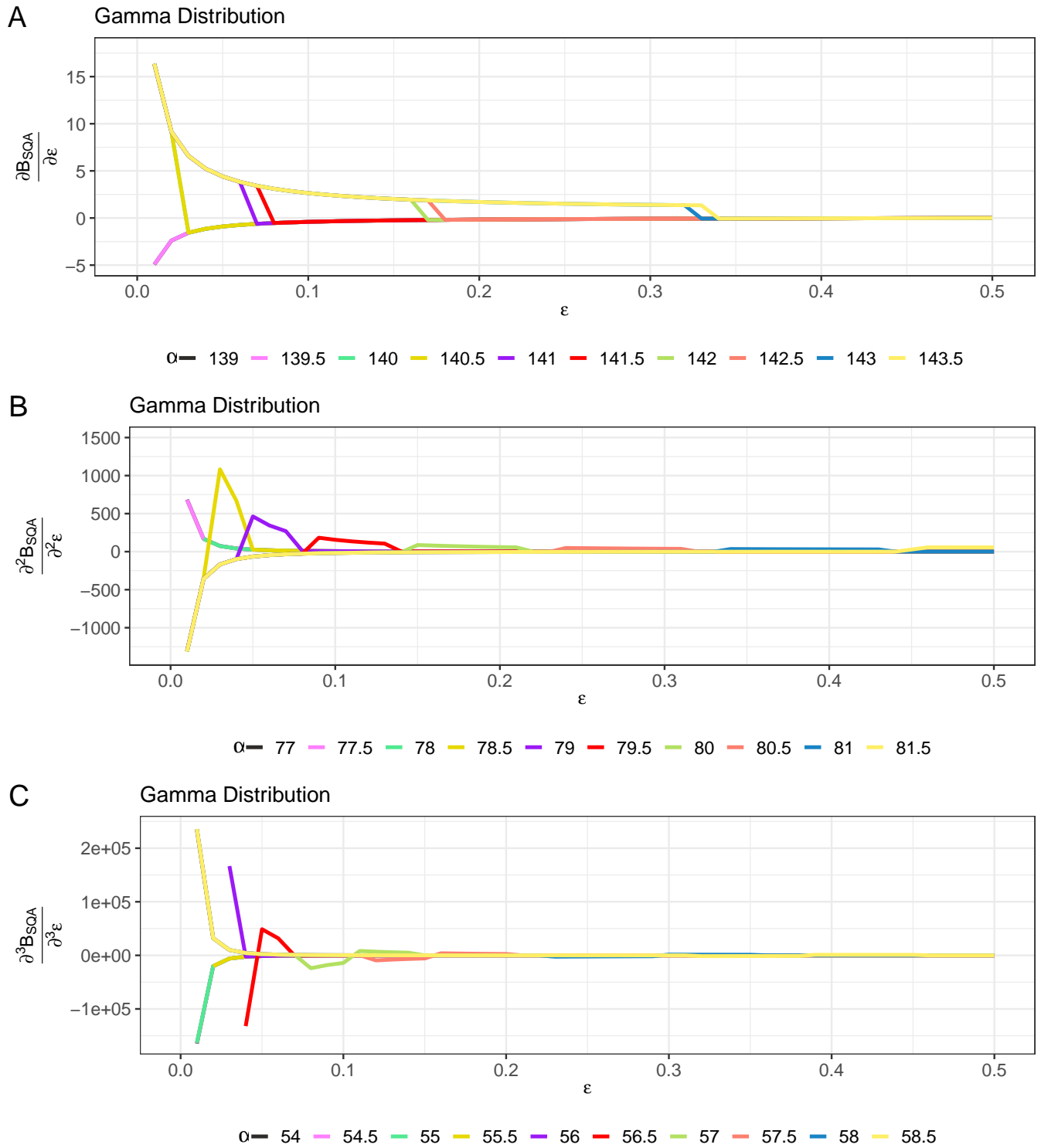


Fig. S2. A. The first derivative of the bias function of SQA for the gamma distribution as a function of the breakdown point ϵ . B. The second derivative of the bias function of SQA for the gamma distribution as a function of the breakdown point ϵ . C. The third derivative of the bias function of SQA for the gamma distribution as a function of the breakdown point ϵ .

111 **Theorem 0.7.** *The above bias bound function, $B_{STMB}(\epsilon)$, is monotonic increasing with respect to ϵ over the interval $(0, \frac{1}{2})$.*

112 *Proof.*
$$\frac{dB_{STMB}(\epsilon)}{d\epsilon} = \frac{2\sqrt{6}(-5832\epsilon^7 + 232(\sqrt{9\epsilon^2+4}-2)\epsilon + 32(\sqrt{9\epsilon^2+4}-2) + 324(6\sqrt{9\epsilon^2+4}-25)\epsilon^6)}{(1-2\epsilon)^2\sqrt{9\epsilon^2+4}(-243\epsilon^4+18(4\sqrt{9\epsilon^2+4}-9)\epsilon^2+36(\sqrt{9\epsilon^2+4}-2)\epsilon+8(\sqrt{9\epsilon^2+4}-2)+27(3\sqrt{9\epsilon^2+4}-8)\epsilon^3)^{3/2} +}$$

113
$$\frac{2\sqrt{6}(2(397\sqrt{9\epsilon^2+4}-830)\epsilon^2+54(50\sqrt{9\epsilon^2+4}-171)\epsilon^5+9(294\sqrt{9\epsilon^2+4}-779)\epsilon^4+9(193\sqrt{9\epsilon^2+4}-444)\epsilon^3)}{(1-2\epsilon)^2\sqrt{9\epsilon^2+4}(-243\epsilon^4+18(4\sqrt{9\epsilon^2+4}-9)\epsilon^2+36(\sqrt{9\epsilon^2+4}-2)\epsilon+8(\sqrt{9\epsilon^2+4}-2)+27(3\sqrt{9\epsilon^2+4}-8)\epsilon^3)^{3/2}}.$$

114 Let $g(\epsilon) = -5832\epsilon^7 + 2(397\sqrt{9\epsilon^2+4}-830)\epsilon^2 + 232(\sqrt{9\epsilon^2+4}-2)\epsilon + 32(\sqrt{9\epsilon^2+4}-2) + 324(6\sqrt{9\epsilon^2+4}-25)\epsilon^6 +$
 115 $54(50\sqrt{9\epsilon^2+4}-171)\epsilon^5 + 9(294\sqrt{9\epsilon^2+4}-779)\epsilon^4 + 9(193\sqrt{9\epsilon^2+4}-444)\epsilon^3$ and $h(\epsilon)$ denotes the common denominator
 116 of $\frac{dB_{STMB}(\epsilon)}{d\epsilon}$. Then, for $0 < \epsilon < \frac{1}{2}$, $h(\epsilon) > 0$. To have $g(\epsilon) > 0$, it is equivalent to $2 \times 397\sqrt{9\epsilon^2+4}\epsilon^2 + 232\sqrt{9\epsilon^2+4}\epsilon +$
 117 $32\sqrt{9\epsilon^2+4} + 324\epsilon^6 \times 6\sqrt{9\epsilon^2+4} + 54\epsilon^5 \times 50\sqrt{9\epsilon^2+4} + 9\epsilon^4 \times 294\sqrt{9\epsilon^2+4} + 9\epsilon^3 \times 193\sqrt{9\epsilon^2+4} > 5832\epsilon^7 + 2 \times 830\epsilon^2 + 2 \times$
 118 $232\epsilon + 32 \times 2 + 25 \times 324\epsilon^6 + 54\epsilon^5 \times 171 + 9\epsilon^4 \times 779 + 444 \times 9\epsilon^3$. Squaring the left and right sides and then expanding, it
 119 is equivalent to $34012224\epsilon^{14} + 94478400\epsilon^{13} + 173315376\epsilon^{12} + 231367104\epsilon^{11} + 245524284\epsilon^{10} + 213603804\epsilon^9 + 155238849\epsilon^8 +$
 120 $94957380\epsilon^7 + 48836664\epsilon^6 + 20951856\epsilon^5 + 7364752\epsilon^4 + 2051968\epsilon^3 + 427776\epsilon^2 + 59392\epsilon + 4096 > 34012224\epsilon^{14} + 94478400\epsilon^{13} +$
 121 $173315376\epsilon^{12} + 231367104\epsilon^{11} + 245454300\epsilon^{10} + 213576588\epsilon^9 + 155256345\epsilon^8 + 94952088\epsilon^7 + 48850488\epsilon^6 + 20954880\epsilon^5 + 7361296\epsilon^4 +$
 122 $2051968\epsilon^3 + 427776\epsilon^2 + 59392\epsilon + 4096 \iff 69984\epsilon^{10} + 27216\epsilon^9 - 17496\epsilon^8 + 5292\epsilon^7 - 13824\epsilon^6 - 3024\epsilon^5 + 3456\epsilon^4 > 0 \iff$
 123 $108(1-2\epsilon)^2\epsilon^4(162\epsilon^4 + 225\epsilon^3 + 144\epsilon^2 + 100\epsilon + 32) > 0$. Then just need $162\epsilon^4 + 225\epsilon^3 + 144\epsilon^2 + 100\epsilon + 32 > 0$. Since
 124 $144\epsilon^2 + 100\epsilon + 32 > 0$ is valid for any $\epsilon \in \mathbb{R}$, $g(\epsilon) > 0$ is valid for any $\epsilon > 0$. So, $\frac{dB_{STMB}(\epsilon)}{d\epsilon} > 0$, which leads to the assertion of
 125 the theorem. \square

126 Another interesting case is when $\gamma = 2$, setting the $\mu = 0$, $\sigma = 1$, $\sup_{P \in \mathcal{P}_U}(RVaR_{\alpha=\epsilon, \beta=1-2\epsilon}) = \frac{\sqrt{\epsilon(3\epsilon+8)}}{3}$, obviously
 127 monotonic, and $\inf_{P \in \mathcal{P}_U}(RVaR_{\alpha=\epsilon, \beta=1-2\epsilon}) = -\frac{\sqrt{(2\epsilon)(8+6\epsilon)}}{3}$, also obviously monotonic.

128 **SI Dataset S1 (dataset_one.xlsx)**

129 Raw data of asymptotic bias of all estimators shown in Figure 1 in the main text.

130 **References**

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