

# ON SHRINKAGE ESTIMATION FOR THE SCALE PARAMETER OF WEIBULL DISTRIBUTION

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## ABSTRACT

In the present article, some shrinkage estimators for the scale parameter of a two – parameter Weibull life testing model have been suggested under the LINEX loss function assuming the shape parameter is to be known. The comparisons of the proposed estimators have been made with the improved estimator.

**Keywords:** Scale Parameter, Weibull distribution, Shrinkage estimator and factor, MSE, Asymmetric loss function, Level of significance.

### Notations

$\beta, \alpha$	Weibull scale and shape parameter
$\beta_0$	Hypothetical value of $\beta$
$\hat{\beta}_u$	Unbiased estimate of $\beta$
$\hat{\beta}$	MLE estimate of $\beta$
$a$	Shape parameter of the LINEX loss function
MLE	Maximum likelihood estimate
MSE	Mean square error
$\Delta^*$	$\left( \frac{\hat{\beta}_u}{\beta} - 1 \right)$
$\gamma_i$	$\Gamma\left(n + \frac{i}{a}\right) \quad \forall i = 0, 1.$
$I(u_1, u_2, v)$	$\int_{u_1}^{u_2} (v) \cdot \frac{e^{-w} w^{n-1}}{\gamma_0} dw ; v \text{ may be a function of } w$
$\delta$	$\frac{\beta_0}{\beta}$
$f_0$	$a c_1 \frac{\gamma_0}{\gamma_1} w^{\frac{1}{a}}$
$f_i$	$k_i \left( \frac{\gamma_0}{\gamma_1} w^{\frac{1}{a}} - \delta \right) ; \forall i = 1, 2, 3, 4.$
$w_i$	$\frac{l_i \delta^a}{2} ; \forall i = 1, 2.$

## 1 INTRODUCTION

The Weibull distribution is used in a great variety of applications such as models for life (Weibull, 1951), survival analysis (Berrettoni, 1964), strength, and other properties of many products and materials. Mittnik and Reachev (1993) found that the two – parameter Weibull distribution might be an adequate statistical model for stock returns. In addition, it has been used as a model for diverse items such as ball bearings (Lielein & Zelen, 1956), vacuum tubes (Kao, 1959), and electrical isolation (Nelson, 1972).

The probability density function of the two-parameter Weibull distribution is given by

$$f(x; \beta, \alpha) = \frac{\alpha}{\beta^\alpha} x^{(\alpha-1)} \exp\left[-\left(\frac{x}{\beta}\right)^\alpha\right] ; x > 0, \beta > 0, \alpha > 0. \quad (1.1)$$

Let  $x_1, x_2, \dots, x_n$  be the life times of  $n$  items put to test under the Weibull failure model (1.1). Then

$$\hat{\beta} = \left[ \frac{1}{n} \sum_{i=1}^n x_i^\alpha \right]^{\frac{1}{\alpha}} \text{ and } \hat{\beta}_u = n^{\frac{1}{\alpha}} \frac{\gamma_0}{\gamma_1} \hat{\beta}. \quad (1.2)$$

The estimator  $\hat{\beta}$  follows a Gamma distribution with the probability density function

$$f(\hat{\beta}) = \frac{\alpha}{\gamma_0} \left[ \frac{n}{\beta^\alpha} \right]^n \hat{\beta}^{(n\alpha-1)} \exp\left[-n\left(\frac{\hat{\beta}}{\beta}\right)^\alpha\right] ; \hat{\beta} \geq 0. \quad (1.3)$$

For the special case  $\alpha = 1$ , the Weibull distribution is the exponential distribution. For  $\alpha = 2$ , it is the Rayleigh distribution. For shape parameter values in the range  $3 \leq \alpha \leq 4$ , the shape of the Weibull distribution is close to that of normal distribution, and for a large values of  $\alpha$ , say  $\alpha \geq 10$ , the shape of the Weibull distribution is close to that of the smallest extreme value distribution.

Thompson (1968) suggested a shrinkage estimator  $k(\hat{\theta} - \theta_0) + \theta_0$  for any parameter  $\theta$  and showed that it is more efficient than any usual estimator  $\hat{\theta}$  when  $\theta$  is in the vicinity of  $\theta_0$ , a guess value of  $\theta$ . The shrinkage factor  $k \in [0, 1]$  is specified by the experimenter according to his belief in  $\theta_0$ . The shrinkage procedure has been applied in numerous problems, including mean survival time in epidemiological studies (Harries & Shakarki, 1979), forecasting of the money supply (Tso, 1990), estimating mortality rates (Marshall, 1991), and improved estimation in sample surveys (Wooff, 1985).

Following Basu and Ebrahimi (1991), the invariant form of the LINEX loss function for  $\hat{\beta}_u$  is defined as

$$L(\Delta^*) = e^{a\Delta^*} - a\Delta^* - 1 ; a \neq 0. \quad (1.4)$$

The shape of this loss function is determined by the value of 'a' (the sign of 'a' reflects the direction of asymmetry,  $a > 0$  ( $a < 0$ ) if overestimation is more (less) serious than the underestimation) and its magnitude reflects the degree of asymmetry.

Pandey et al. (1989) have considered some shrinkage estimator for the shape parameter of the Weibull distribution under the squared error loss function. Singh and Shukla (2000), Montanari et al. (1997), and Hisada and Arizino (2002) have considered the Weibull distribution in different contexts. Pandey and Upadhyay (1985), Nigm (1989), and Dellaportas and Wright (1991) have considered predication problems in two-parameter Weibull distribution. Recently, Prakash and Singh (2008 b) have studied the properties of the Bayes' estimator of the lifetime parameters for two-parameter Weibull distribution. Zellner (1986), Singh et al. (2002), Ahmadi et al.

(2005), Prakash and Singh (2006, 2008 a), Singh et al. (2007), and others have used the LINEX loss function in various estimation and prediction problems.

This paper deals with the some shrinkage estimators for the scale parameter of the two – parameter Weibull distribution when a prior guess value of the scale parameter is available. Assuming the shape parameter is to be known, the relative efficiencies of the proposed estimators are studied with respect to improved estimator of  $\hat{\beta}_u$ .

## 2 A CLASS OF ESTIMATORS AND THEIR PROPERTIES

The proposed class of estimators for the unbiased estimator of the parameter  $\beta$  is given by

$$P = c \hat{\beta}_u, \text{ where } c \text{ is a constant.} \quad (2.1)$$

The invariant form of the LINEX loss for the class  $P$  is

$$L(P) = \exp\left[a\left(\frac{c\hat{\beta}_u}{\beta} - 1\right)\right] - a\left(\frac{c\hat{\beta}_u}{\beta} - 1\right) - 1$$

and the risk under the invariant form of the LINEX loss is

$$R(P) = e^{-a} I\left(0, \infty, \left(\exp\left(a c \frac{\gamma_0}{\gamma_1} w^{\frac{1}{a}}\right)\right)\right) + (a - 1 - a c). \quad (2.2)$$

The value of  $c = c_1$  (say), which minimizes the  $R(P)$ , can be obtained by solving the equation

$$I\left(0, \infty, \left(\exp\left(a c \frac{\gamma_0}{\gamma_1} w^{\frac{1}{a}}\right) w^{\frac{1}{a}}\right)\right) = \gamma_1 e^a \quad (2.3)$$

for a given set of values for  $n, \alpha$  and 'a' as considered in later calculation.

The minimum risk estimator among the class  $P$  is  $P_1 = c_1 \hat{\beta}_u$  with the minimum risk under the invariant form of the LINEX loss

$$R(P_1) = e^{-a} I\left(0, \infty, e^{af_0}\right) - (a - 1 - a c_1). \quad (2.4)$$

Following Thompson (1968), the shrinkage estimator for  $\hat{\beta}_u$  is given by

$$Y = k(\hat{\beta}_u - \beta_0) + \beta_0. \quad (2.5)$$

The value of the shrinkage factor  $k = k_1$  (say), which minimizes the risk of  $Y$  under the invariant form of the LINEX loss, may be obtained by solving the equation

$$I\left(0, \infty, \frac{f'}{k} \exp\left(a f'\right)\right) = (1 - \delta) e^{a(1-\delta)}; f' = k\left(\frac{\gamma_0}{\gamma_1} w^{\frac{1}{a}} - \delta\right). \quad (2.6)$$

for a given set of values for  $n, \alpha, 'a'$  and  $\delta$  as considered in later calculation.

The shrinkage estimator  $Y_1$  having minimum risk in the class  $\mathbf{Y}$  is

$$Y_1 = k_1(\hat{\beta}_u - \beta_0) + \beta_0 \quad (2.7)$$

with the minimum risk under the invariant form of LINEX loss

$$R(Y_1) = e^{-a(\delta-1)} I(0, \infty, e^{af_1}) + a(k_1 - 1)(\delta - 1) - 1. \quad (2.8)$$

### 3 CONCLUSION

The relative bias for the improved shrinkage estimator  $Y_1$  is obtained as

$$RB(Y_1) = \frac{1}{\beta} (E(Y_1) - \beta) = (1 - k_1)(\delta - 1). \quad (3.1)$$

This expression clearly shows that the relative bias is zero at  $\delta = 1$  and has a tendency of being negative for  $0 < \delta < 1$  and positive for  $\delta > 1$ .

The relative efficiency for the shrinkage estimator  $Y_1$  with respect to the minimum class of estimators  $P_1$  under the invariant form of the LINEX loss is defined as

$$RE(Y_1, P_1) = \frac{R(P_1)}{R(Y_1)}. \quad (3.2)$$

The expression of  $RE(Y_1, P_1)$  is a function of  $\delta$ ,  $a$ ,  $n$  and  $\alpha$ . For the selected set of values of  $n = 04, 08, 12, 15$ ;  $a = 0.25, 0.50, 1.00, 1.50$ ;  $\delta = 0.40 (0.20) 1.80$  and  $\alpha = 2$ , the values of  $RE(Y_1, P_1)$  have been calculated (not presented here), and it is observed that the shrinkage estimator  $Y_1$  is more efficient than the improved estimator  $P_1$  when  $\beta_0$  is in the vicinity of  $\beta$ . More specifically, the shrinkage estimator  $Y_1$  is more efficient than  $P_1$  when  $0.40 \leq \delta \leq 1.60$  and attains maximum efficiency at the point  $\delta = 1.00$ . The effective interval decreases as  $n$  increases and for fixed  $n$ , as ' $a$ ' increases, the relative efficiency first increases for  $\delta < 1.00$  and then decreases.

### 4 THE SHRINKAGE TESTIMATORS AND THEIR PROPERTIES

We have seen that the shrinkage estimator  $Y_1$  has smaller risk than the estimator  $P_1$  when a hypothetical value of the parameter is in the vicinity of the true value. This suggests that when  $\beta_0$  for  $\beta$  is given, the hypothesis  $H_0: \beta = \beta_0$  against  $H_1: \beta \neq \beta_0$  is carried out first and upon the acceptance of the  $H_0$ , the shrinkage estimator  $Y_1$  is used as an estimator for  $\beta$ ; otherwise  $P_1$  as an estimator for  $\beta$ . Thus the proposed shrinkage estimator for  $\beta$  is given by

$$T_1 = \begin{cases} k_1(\hat{\beta}_u - \beta_0) + \beta_0 & \text{if } t_1 \leq \hat{\beta}_u \leq t_2 \\ c_1 \hat{\beta}_u & \text{otherwise} \end{cases}, \quad (4.1)$$

where  $t_1 = \frac{\gamma_0}{\gamma_1} \left( \frac{\beta_0^\alpha l_1}{2} \right)^{\frac{1}{\alpha}}$ ,  $t_2 = \frac{\gamma_0}{\gamma_1} \left( \frac{\beta_0^\alpha l_2}{2} \right)^{\frac{1}{\alpha}}$  and  $l_1, l_2$  being the values of the lower and upper

$100(\varepsilon/2)\%$  points of the chi-square distribution with  $2n$  degrees of freedom at  $\varepsilon$  level of significance.

The expressions of the relative bias and risk under the invariant form of the LINEX loss for the proposed shrinkage estimator are obtained as

$$RB(T_1) = I(w_1, w_2, (f_1 - f_0 + \delta)) + c_1 - 1 \quad (4.2)$$

and

$$\begin{aligned} R(T_1) &= e^{a(\delta-1)} I(w_1, w_2, e^{af_1}) + e^{-a} I(0, \infty, e^{af_0}) - e^{-a} I(w_1, w_2, e^{af_0}) \\ &\quad + a I(w_1, w_2, (f_0 - f_1 - \delta)) + a(1 - c_1) - 1. \end{aligned} \quad (4.3)$$

Waikar et al. (1984) have suggested the idea of taking shrinkage factor as a function of the test statistic. Under  $H_0: \beta = \beta_0$

$$l_1 \leq 2n \left( \frac{\hat{\beta}}{\beta_0} \right)^a \leq l_2 \Leftrightarrow 0 \leq \frac{1}{l_2 - l_1} \left( 2n \left( \frac{\hat{\beta}}{\beta_0} \right)^a - l_1 \right) = k_2 \text{ (say)} \leq 1. \quad (4.4)$$

Based upon this shrinkage factor  $k_2$ , the shrinkage estimator is given by

$$T_2 = \begin{cases} k_2(\hat{\beta}_u - \beta_0) + \beta_0 & \text{if } t_1 \leq \hat{\beta}_u \leq t_2 \\ c_1 \hat{\beta}_u & \text{otherwise} \end{cases}. \quad (4.5)$$

When  $H_0: \beta = \beta_0$  is accepted,  $l_1 \leq 2n \leq l_2 \Rightarrow \frac{l_1}{2n} \leq 1$ . If there is interest in smaller values of the

shrinkage factor  $k$ , then one can use  $\frac{l_1}{2n} \leq 1$ . Thus the shrinkage estimator is given by

$$T_3 = \begin{cases} k_3(\hat{\beta}_u - \beta_0) + \beta_0 & \text{if } t_1 \leq \hat{\beta}_u \leq t_2 \\ c_1 \hat{\beta}_u & \text{otherwise} \end{cases}. \quad (4.6)$$

Here  $k_3 = \frac{2n}{l_2 - l_1} \left| \left( \frac{\hat{\beta}}{\beta_0} \right)^a - 1 \right|$ , it may possible that the value of the shrinkage factor is negative, so we make it positive. Adke et al. (1987) and Pandey et al. (1988) have considered this type of shrinkage factor.

As the value of  $c_1$  also lies between zero and one, it may be a choice for the shrinkage factor. Based on this, the shrinkage estimator is defined as

$$T_4 = \begin{cases} c_1(\hat{\beta}_u - \beta_0) + \beta_0 & \text{if } t_1 \leq \hat{\beta}_u \leq t_2 \\ c_1 \hat{\beta}_u & \text{otherwise} \end{cases}. \quad (4.7)$$

The expressions of the relative biases and risk under the invariant form of the LINEX loss function for these shrinkage estimators are given as

$$RB(T_i) = I(w_1, w_2, (f_i - f_0 + \delta)) + c_1 - 1 \quad (4.8)$$

and

$$R(T_i) = e^{a(\delta-1)} I(w_1, w_2, e^{af_i}) + e^{-a} I(0, \infty, e^{af_0}) - e^{-a} I(w_1, w_2, e^{af_0})$$

$$+ a I(w_1, w_2, (f_0 - f_i - \delta)) + a(1 - c_1) - 1; \quad (4.9)$$

where  $k_4 = c_1$  (say) and  $i = 2, 3, 4$ .

## 5 CONCLUSION AND RECOMMENDATIONS

The relative efficiencies of  $T_i ; i = 1, 2, \dots, 4$ , with respect to the minimum risk estimator  $P_1$  are given by,

$$RE(T_i, P_1) = \frac{R(P_1)}{R(T_i)} ; i = 1, \dots, 4.$$

The expressions of the relative biases and the  $RE(T_i, P_1); i = 1, \dots, 4$  are the function of  $\delta$ ,  $a$ ,  $n$ ,  $\alpha$  and  $\varepsilon$ . The Tables 1 – 4 show the values of  $RE(T_i, P_1); i = 1, \dots, 4$  for the same set of values of  $\delta$ ,  $a$ ,  $n$  and  $\alpha$  as considered earlier with  $\varepsilon = 0.01$  and  $0.05$ . The numerical findings are presented here only for the relative efficiency.

The relative biases are negligibly small and lie between -0.043 to 0.056 for the estimator  $T_1$  and -0.039 to 0.02 for estimator  $T_2$ . The absolute values of biases decrease as the sample size  $n$  increases. Further,  $|RB(T_2)|$  increases when level of significance  $\varepsilon$  increases in  $0.50 \leq \delta \leq 1.00$  and decreases otherwise. A similar trend has been seen for  $T_1$  when  $0.50 \leq \delta \leq 0.90$ . The relative bias of  $T_3$  lies between -0.038 to 0.027 and for  $T_4$  in -0.045 to 0.212 and are negligible small. The absolute values of biases decrease as the sample size  $n$  increases. In addition,  $|RB(T_3)|$  increases as  $\varepsilon$  increases in  $0.50 \leq \delta \leq 0.90$  and decreases otherwise. On the other hand,  $|RB(T_4)|$  decreases as  $\varepsilon$  increases except for  $\delta = 1$ .

The shrinkage estimators  $T_1$  and  $T_4$  perform better for all considered values of the parametric space. On the other hand, the shrinkage estimators  $T_2$  and  $T_3$  are efficient when  $0.40 \leq \delta \leq 1.40$ . All the shrinkage estimators attain maximum efficiency at the point  $\delta = 1.00$ . For fixed  $\varepsilon$  and 'a', as the sample size increases, the relative efficiency decreases in  $0.40 \leq \delta \leq 1.60$  for the estimators  $T_1$  and  $T_3$  whereas it decreases for  $T_2$  in the entire range of  $\delta$ . For the shrinkage estimator  $T_4$ , the relative efficiency decreases as  $n$  increases when  $\delta < 1$ .

**Table 1.** Relative efficiency of estimators  $T_1 - T_4$  for  $n=4$  items for a variety of  $\varepsilon$ ,  $\delta$ , and 'a' parameters

$\varepsilon = 0.01$		$\delta$							
a	n = 04	0.40	0.60	0.80	1.00	1.20	1.40	1.60	1.80
0.25	$T_1$	1.0388	1.4231	2.9039	23.129	3.2006	1.7112	1.4369	1.3442
	$T_2$	1.0436	2.8075	8.7184	15.045	5.5219	2.8115	0.7667	0.3997
	$T_3$	1.0291	2.2053	6.2012	31.971	6.8515	2.7527	1.3971	0.8760
	$T_4$	1.0326	1.8530	2.4589	2.7623	2.0545	1.8572	1.6698	1.4687
0.50	$T_1$	1.0384	1.4209	2.9474	24.472	3.1285	1.6562	1.3925	1.3045
	$T_2$	1.0420	2.7816	8.6197	14.689	5.3343	2.7392	0.7257	0.3720
	$T_3$	1.0283	2.1939	6.1556	32.208	6.6751	2.6465	1.3287	0.8253
	$T_4$	1.0321	1.8600	2.5152	2.8492	2.0502	1.8215	1.6125	1.3974
1.00	$T_1$	1.0348	1.4011	2.8664	22.557	2.8514	1.4842	1.2511	1.1816
	$T_2$	1.0391	2.7328	8.3030	14.271	4.7606	2.5356	0.6222	0.3075
	$T_3$	1.0262	2.1619	5.9448	30.516	6.0623	2.3439	1.1501	0.6998
	$T_4$	1.0297	1.8376	2.5364	2.8139	1.9111	1.6631	1.4514	1.2436
1.50	$T_1$	1.0326	1.3930	2.9160	24.556	2.7010	1.3731	1.2267	1.0961
	$T_2$	1.0365	2.6884	8.0946	14.490	4.3963	2.4018	0.5505	0.2615
	$T_3$	1.0248	2.1404	5.8359	30.504	5.7097	2.1469	1.0278	0.6114
	$T_4$	1.0286	1.8415	2.5548	2.9433	1.8629	1.5648	1.3269	1.1077
$\varepsilon = 0.05$									
0.25	$T_1$	1.0158	1.2276	2.5369	20.555	3.4577	1.7466	1.4176	1.3063
	$T_2$	1.0175	2.2503	5.3586	26.547	7.3278	3.0179	0.8259	0.4218
	$T_3$	1.0144	1.9357	4.2464	21.452	7.5991	3.2837	1.8379	1.2641
	$T_4$	1.0138	1.6206	2.5293	3.0479	2.3386	1.8986	1.6464	1.4191
0.50	$T_1$	1.0153	1.2239	2.5323	22.007	3.4097	1.6973	1.3770	1.2743
	$T_2$	1.0167	2.2348	5.2537	25.852	7.1283	2.9416	0.7835	0.3935
	$T_3$	1.0138	1.9248	4.1779	21.276	7.4640	3.1655	1.7527	1.1965
	$T_4$	1.0135	1.6208	2.5744	3.1663	2.3622	1.8683	1.5921	1.3534
1.00	$T_1$	1.0140	1.2115	2.4577	20.442	3.1194	1.5302	1.2426	1.1589
	$T_2$	1.0154	2.2093	5.0861	24.043	6.4299	2.7213	0.6747	0.3268
	$T_3$	1.0127	1.9047	4.0512	20.473	6.8594	2.8158	1.5249	1.0242
	$T_4$	1.0124	1.6063	2.5336	3.1032	2.2343	1.7154	1.4379	1.2109
1.50	$T_1$	1.0131	1.2039	2.4346	22.456	2.9987	1.4269	1.2038	1.0837
	$T_2$	1.0142	2.1842	4.9117	22.679	6.0204	2.5782	0.5995	0.2791
	$T_3$	1.0118	1.8868	3.9330	19.971	6.5513	2.5907	1.3690	0.9027
	$T_4$	1.0118	1.6033	2.5885	3.2823	2.2320	1.6261	1.3182	1.0828

**Table 2.** Relative efficiency of estimators  $T_1 - T_4$  for  $n=8$  items for a variety of  $\varepsilon$ ,  $\delta$ , and 'a' parameters

$\varepsilon = 0.01$		$\delta$							
a	n = 08	0.40	0.60	0.80	1.00	1.20	1.40	1.60	1.80
0.25	$T_1$	1.0007	1.0692	1.7534	10.113	2.1249	1.3952	1.2663	1.2185
	$T_2$	1.0008	1.9249	4.0749	12.988	3.7909	1.9612	0.3600	0.1761
	$T_3$	1.0005	1.6643	3.1006	19.502	3.3278	1.4490	0.8452	0.6015
	$T_4$	1.0006	1.4543	2.3680	2.8256	2.1000	1.8675	1.6830	1.4765
0.50	$T_1$	1.0007	1.0720	1.8360	12.757	2.1973	1.4311	1.3024	1.2564
	$T_2$	1.0008	1.9227	4.1165	14.281	3.9223	1.9816	0.3619	0.1739
	$T_3$	1.0005	1.6664	3.1555	22.489	3.4523	1.4791	0.8555	0.6052
	$T_4$	1.0006	1.4575	2.4863	3.1678	2.2404	1.9329	1.6938	1.4440
1.00	$T_1$	1.0006	1.0705	1.8655	14.575	2.1519	1.3901	1.2248	1.2345
	$T_2$	1.0007	1.9155	4.0733	13.636	3.8111	1.9344	0.3335	0.1542
	$T_3$	1.0004	1.6638	3.1416	24.092	3.3737	1.4065	0.7993	0.5582
	$T_4$	1.0006	1.4553	2.4252	3.3891	2.2629	1.8860	1.6078	1.3369
1.50	$T_1$	1.0006	1.0685	1.8728	15.827	2.0764	1.3314	1.1759	1.1969
	$T_2$	1.0006	1.9085	4.0144	12.610	3.6456	1.8761	0.3020	0.1340
	$T_3$	1.0004	1.6605	3.1105	24.944	3.2471	1.3172	0.7345	0.5056
	$T_4$	1.0006	1.4522	2.4913	3.5327	2.2368	1.8064	1.5048	1.2266
$\varepsilon = 0.05$									
0.25	$T_1$	1.0002	1.0255	1.4727	9.5107	2.4519	1.4155	1.2310	1.1313
	$T_2$	1.0002	1.8216	2.7596	14.814	5.6484	2.0723	0.3755	0.1799
	$T_3$	1.0002	1.6198	2.4840	11.723	3.7168	1.7997	1.2264	1.0192
	$T_4$	1.0002	1.3915	1.8741	3.2563	2.4978	1.8999	1.6259	1.3381
0.50	$T_1$	1.0002	1.0260	1.4899	11.516	2.5966	1.4585	1.2673	1.1684
	$T_2$	1.0002	1.8201	2.7458	15.388	5.9607	2.0975	0.3779	0.1778
	$T_3$	1.0002	1.6184	2.4693	12.264	3.9142	1.8446	1.2467	1.0325
	$T_4$	1.0002	1.3922	1.9091	3.6549	2.7329	1.9731	1.6357	1.3097
1.00	$T_1$	1.0001	1.0251	1.4850	12.471	2.6003	1.4255	1.2092	1.1577
	$T_2$	1.0002	1.8168	2.7067	15.166	5.9018	2.0489	0.3491	0.1579
	$T_3$	1.0002	1.6156	2.4320	12.249	3.8859	1.7661	1.1754	0.9676
	$T_4$	1.0001	1.3910	1.9136	3.9108	2.8332	1.9350	1.5578	1.2234
1.50	$T_1$	1.0001	1.0239	1.4746	12.847	2.5538	1.3737	1.1566	1.1325
	$T_2$	1.0001	1.8139	2.6689	14.759	5.7354	1.9874	0.3169	0.1373
	$T_3$	1.0001	1.6129	2.3965	12.064	3.7892	1.6642	1.0894	0.8904
	$T_4$	1.0001	1.3895	1.9080	4.0734	2.8653	1.8627	1.4632	1.1330

**Table 3.** Relative efficiency of estimators  $T_1 - T_4$  for  $n=12$  items for a variety of  $\epsilon$ ,  $\delta$ , and 'a' parameters

$\epsilon = 0.01$		$\delta$							
a	n = 12	0.40	0.60	0.80	1.00	1.20	1.40	1.60	1.80
0.25	$T_1$	1.0000	1.0107	1.3810	9.0131	1.8983	1.3356	1.2558	1.2103
	$T_2$	1.0000	1.7897	2.6631	11.839	3.3273	1.6866	0.2362	0.1110
	$T_3$	1.0000	1.5872	2.2885	14.802	2.3208	1.1252	0.7520	0.6090
	$T_4$	1.0000	1.3737	1.9624	4.1537	2.6504	2.1825	1.8657	1.5273
0.50	$T_1$	1.0000	1.0103	1.3698	8.7289	1.8437	1.3008	1.2232	1.1835
	$T_2$	1.0000	1.7890	2.6460	11.582	3.2192	1.6577	0.2226	0.1027
	$T_3$	1.0000	1.5867	2.2739	14.490	2.2457	1.0776	0.7156	0.5776
	$T_4$	1.0000	1.3732	1.9514	4.1134	2.5862	2.1133	1.7999	1.4713
1.00	$T_1$	1.0000	1.0100	1.3804	9.7685	1.8232	1.2863	1.2101	1.1765
	$T_2$	1.0000	1.7880	2.6337	12.161	3.1721	1.6320	0.2066	0.0916
	$T_3$	1.0000	1.5862	2.2665	15.531	2.2113	1.0347	0.6781	0.5432
	$T_4$	1.0000	1.3724	1.9489	4.3748	2.6178	2.0677	1.7192	1.3779
1.50	$T_1$	1.0000	1.0096	1.3767	10.024	1.7617	1.2382	1.1525	1.1459
	$T_2$	1.0000	1.7869	2.6113	12.185	3.0462	1.5930	0.1868	0.0793
	$T_3$	1.0000	1.5855	2.2489	15.729	2.1231	1.0696	0.6264	0.4976
	$T_4$	1.0000	1.3716	1.9366	4.4644	2.5641	1.9733	1.6148	1.2793
$\epsilon = 0.05$									
0.25	$T_1$	1.0000	1.0026	1.1794	6.9721	2.3640	1.3564	1.2046	1.0721
	$T_2$	1.0000	1.7727	2.1018	8.0810	5.4666	1.7601	0.2404	0.1133
	$T_3$	1.0000	1.5776	1.9338	7.6355	2.7304	1.4393	1.1536	1.1180
	$T_4$	1.0000	1.3612	1.5852	3.6812	3.4603	2.2225	1.7488	1.2633
0.50	$T_1$	1.0000	1.0025	1.1679	6.7855	2.3031	1.3229	1.1785	1.0475
	$T_2$	1.0000	1.7725	2.0944	7.9461	5.3071	1.7291	0.2267	0.1048
	$T_3$	1.0000	1.5774	1.9262	7.5270	2.6554	1.3853	1.1074	1.0766
	$T_4$	1.0000	1.3611	1.5803	3.6472	3.3954	2.1557	1.6932	1.2274
1.00	$T_1$	1.0000	1.0024	1.1713	7.0083	2.3346	1.3128	1.1698	1.0535
	$T_2$	1.0000	1.7722	2.0837	7.9268	5.3496	1.7028	0.2106	0.0935
	$T_3$	1.0000	1.5770	1.9120	7.5359	2.6608	1.3436	1.0660	1.0391
	$T_4$	1.0000	1.3609	1.5756	3.7547	3.5276	2.1180	1.6250	1.1652
1.50	$T_1$	1.0000	1.0023	1.1679	6.9191	2.2942	1.2697	1.1383	1.0356
	$T_2$	1.0000	1.7718	2.0720	7.7809	5.2146	1.6613	0.1906	0.0809
	$T_3$	1.0000	1.5766	1.8986	7.4238	2.5882	1.2707	1.0001	0.9779
	$T_4$	1.0000	1.3606	1.5687	3.7680	3.5221	2.0293	1.5345	1.0974

**Table 4.** Relative efficiency of estimators  $T_1 - T_4$  for  $n=12$  items for a variety of  $\epsilon$ ,  $\delta$ , and 'a' parameters

$\epsilon = 0.01$		$\delta$							
a	n = 15	0.40	0.60	0.80	1.00	1.20	1.40	1.60	1.80
0.25	$T_1$	1.0000	1.0020	1.1883	6.2381	1.6409	1.2275	1.1616	1.1151
	$T_2$	1.0000	1.7717	2.1949	8.1917	2.8204	1.5138	0.1679	0.0773
	$T_3$	1.0000	1.5753	1.9690	9.7082	1.7304	1.0869	0.6777	0.6081
	$T_4$	1.0000	1.3608	1.6955	4.5675	2.9160	2.2982	1.9261	1.5201
0.50	$T_1$	1.0000	1.0020	1.1876	6.0691	1.6258	1.2021	1.1384	1.0973
	$T_2$	1.0000	1.7715	2.1862	8.0437	2.7436	1.4946	0.1589	0.0718
	$T_3$	1.0000	1.5751	1.9607	9.5171	1.6817	1.0728	0.6493	0.5816
	$T_4$	1.0000	1.3607	1.6893	4.5292	2.8515	2.2299	1.8629	1.4697
1.00	$T_1$	1.0000	1.0019	1.1920	6.5635	1.6106	1.1827	1.1258	1.0902
	$T_2$	1.0000	1.7713	2.1830	8.4112	2.7063	1.4747	0.1471	0.0638
	$T_3$	1.0000	1.5750	1.9564	10.070	1.6526	1.0276	0.6169	0.5502
	$T_4$	1.0000	1.3605	1.6825	4.7151	2.8715	2.1746	1.7800	1.3840
1.50	$T_1$	1.0000	1.0018	1.1858	6.3532	1.5427	1.1357	1.0863	1.0579
	$T_2$	1.0000	1.7711	2.1691	8.2266	2.5791	1.4420	0.1319	0.0546
	$T_3$	1.0000	1.5748	1.9430	9.8388	1.5711	1.0339	0.5679	0.5041
	$T_4$	1.0000	1.3603	1.6720	4.6800	2.7658	2.0549	1.6671	1.2916
$\epsilon = 0.05$									
0.25	$T_1$	1.0000	1.0004	1.0756	4.6211	2.0576	1.2421	1.1085	1.0580
	$T_2$	1.0000	1.7681	1.9133	5.2811	4.7292	1.5653	0.1689	0.0803
	$T_3$	1.0000	1.5728	1.7502	5.3810	2.1051	1.1785	1.0241	1.0636
	$T_4$	1.0000	1.3579	1.4674	4.0146	3.2751	2.3401	1.7663	1.1830
0.50	$T_1$	1.0000	1.0004	1.0773	4.5204	2.0500	1.2176	1.0904	1.0543
	$T_2$	1.0000	1.7681	1.9098	5.2087	4.6130	1.5448	0.1599	0.0745
	$T_3$	1.0000	1.5727	1.7462	5.3122	2.0575	1.1424	0.9940	1.0390
	$T_4$	1.0000	1.3579	1.4650	3.9480	3.2481	2.2743	1.7156	1.1545
1.00	$T_1$	1.0000	1.0004	1.0774	4.5979	2.0811	1.2027	1.0808	1.0537
	$T_2$	1.0000	1.7680	1.9060	5.2316	4.6618	1.5242	0.1481	0.0662
	$T_3$	1.0000	1.5727	1.7397	5.3411	2.0612	1.1118	0.9674	1.0197
	$T_4$	1.0000	1.3579	1.4615	4.0737	3.2708	2.2262	1.6491	1.1046
1.50	$T_1$	1.0000	1.0003	1.0741	4.4511	2.0099	1.1581	1.0498	1.0372
	$T_2$	1.0000	1.7680	1.9002	5.1220	4.4827	1.4892	0.1327	0.0566
	$T_3$	1.0000	1.5726	1.7328	5.2362	1.9832	1.0480	0.9119	0.9723
	$T_4$	1.0000	1.3578	1.4574	3.9790	3.2307	2.1107	1.5554	1.0483

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