

RELATIVE EFFICIENCIES OF MAXIMUM LIKELIHOOD, MINIMUM CHI-SQUARE, AND MINIMUM B ESTIMATORS.

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ABSTRACT Debate on the choice between maximum likelihood estimator and minimum chi-square estimator is still on. Rao's school of thought advocates for the maximum likelihood estimator and Berkson's school of thought for the minimum chi-square estimator. In this paper a numerical study has been made by computing the relative efficiency of these estimators together with that of minimum B estimator for the Exponential parameter. The study reveals that for few choices of 'A' and 'B', the constants in Statistic B introduced by Khan and Baily (1987), the minimum B estimator is more efficient than the other two. Also maximum likelihood estimator is more efficient than the minimum chi-square estimator.

1. INTRODUCTION

Khan and Baily(1987) have shown that if X is Poisson random variable with mean μ then $X^{2/3}$ is symmetric about μ and $E(X+A)^{2/3} = \mu^{2/3} + O(\mu^{-1/3})$ and $\text{Var}(X+A)^{2/3} = 4/9(\mu^{1/3}) + O(\mu^{-2/3})$, where A is some constant. Following Fisher's (1922) approach they proposed a new X^2 -type test statistic of goodness of fit as:

$$B = \frac{9}{4} \sum_{r=1}^K \frac{((o_r + A)^{\frac{2}{3}} - (Nf_r[\theta] + B)^{\frac{2}{3}})^2}{(Nf_r[\theta])^{\frac{4}{3}}} \quad (1.1)$$

Where o_r is assumed to be distributed as multinomial with $E(o_r) = Nf_r$, $f_r[\theta]$ is the probability that the observation fall in the r th cell, and A, B are some constants.

Khan (1988a) has shown that the estimator of θ , say $\hat{\theta}_B$ obtained by minimizing statistic B has variance as:

$\text{Var}(\hat{\theta}_B) = \text{Var}(\text{mle}) + O(N^{-2})$ which reduces to $\text{Var}(\text{mle})$ for the choices of $A=B=0.0$ and $A=(3/2)B$, where $\text{Var}(\text{mle})$ is the variance of maximum likelihood estimator of θ obtained by Rao (1962).

In the estimation theory there are differences of opinions on the efficiencies of minimum chi-square estimator and the maximum likelihood estimator. Berkson (1980) went for the minimum chi-square estimate while

Robert and Rao (1993) advocated for maximum likelihood estimate. A numerical study has been carried out to investigate the relative efficiencies of minimum B estimate, minimum chi-square estimate and the maximum likelihood estimate of the parameter of exponential distribution.

2. SUCCESSIVE APPROXIMATION OF MLE, MCSE, AND MBE

Maximum Likelihood Estimate (MLE)

Let a random sample X_1, X_2, \dots, X_N be taken from a distribution $f(x, \theta)$ and categorized in K cells. Let N_r and $N f_r[\theta]$ be the observed and expected frequencies respectively of the observation falling in the r th cell, where $f_r[\theta]$ is the probability of the observation falling in the r th cell. The log likelihood function for the sample observations is defined as:

$$\ln L(x, \theta) = \sum_{r=1}^K N_r \ln f_r[\theta]$$

The MLE say $\hat{\theta}_M$ of θ is the solution of $\frac{\partial \ln L(x, \theta)}{\partial \theta} = 0$. Expressing

$\frac{\partial \ln L(x, \hat{\theta}_M)}{\partial \hat{\theta}_M}$ in Taylor's series about θ_0 up to first two terms we get

$$\frac{\partial \ln L(x, \hat{\theta}_M)}{\partial \hat{\theta}_M} = 0 = \frac{\partial \ln L(x, \theta_0)}{\partial \theta_0} + (\hat{\theta}_M - \theta_0) \frac{\partial^2 \ln L(x, \theta_0)}{\partial \theta_0^2}$$

This gives

$$\hat{\theta}_M = \theta_0 - \left(\frac{\partial \ln L(x, \theta_0)}{\partial \theta_0} \right) / \frac{\partial^2 \ln L(x, \theta_0)}{\partial \theta_0^2} \quad (2.1)$$

The MLE of θ is obtained by successive approximation using (2.1) which give the first approximation $\hat{\theta}_M$ as:

$$\hat{\theta}_M = \theta_0 - \sum_{r=1}^K \left(\frac{N_r f_r'[\theta_0]}{f_r[\theta_0]} \right) / \sum_{r=1}^K \left(-\frac{N_r f_r'[\theta_0]^2}{f_r[\theta_0]^2} + \frac{N_r f_r^{(2)}[\theta_0]}{f_r[\theta_0]} \right) \quad (2.2)$$

Where θ_0 is the initial value.

Minimum Chi-square Estimate (MCSE)

The chi-square statistic of goodness of fit is defined as

$$X^2 = \sum_{r=1}^K \frac{(N_r - N f_r[\theta])^2}{N f_r[\theta]}$$

The MCSE say $\hat{\theta}_c$ of θ is the solution of $\frac{\partial X^2}{\partial \theta} = 0$. Following the above procedure the MCSE is obtained by successive approximation through

$$\hat{\theta}_c = \theta_0 - \left(\frac{\partial X^2}{\partial \theta_0} \right) / \frac{\partial^2 X^2}{\partial \theta_0^2}$$

The first approximation is therefore

$$\hat{\theta}_c = \theta_0 - \sum_{r=1}^K \frac{p_r^2 f_r'[\theta_0]}{f_r[\theta_0]^2} / \sum_{r=1}^K \left(-\frac{2p_r^2 f_r'[\theta_0]^2}{f_r[\theta_0]^3} + \frac{p_r^2 f_r^{(2)}[\theta_0]}{f_r[\theta_0]^2} \right) \quad (2.3)$$

where $p_r = \frac{N_r}{N}$.

Minimum-B Estimate (MBE)

By minimizing the B-statistic of goodness of fit defined in (1.1) can be written as

$$B = \frac{9}{4} \sum_{r=1}^K \frac{((N_r + A)^{\frac{2}{3}} - (N_r f_r[\theta] + B)^{\frac{2}{3}})^2}{(N_r f_r[\theta])^{\frac{1}{3}}}$$

and using the same procedure as above, the MBE is obtained by successive approximation through

$$\hat{\theta}_B = \theta_0 - \left(\frac{\partial B}{\partial \theta_0} \right) / \frac{\partial^2 B}{\partial \theta_0^2} \quad (2.4)$$

So the first approximation of MBE of θ is obtained from

$$\begin{aligned} \hat{\theta}_B = \theta_0 - \sum_{r=1}^K & \left(\frac{(A1 - (B1 + f_r[\theta_0])^{\frac{2}{3}})^2}{f_r[\theta_0]^{\frac{1}{3}}} \right) / \\ & \sum_{r=1}^K \left(\frac{8f_r'[\theta_0]^2}{9f_r[\theta_0]^{\frac{1}{3}}(B1 + f_r[\theta_0])^{\frac{2}{3}}} + \frac{4(A1 - (B1 + f_r[\theta_0])^{\frac{2}{3}})f_r'[\theta_0]^2}{9f_r[\theta_0]^{\frac{1}{3}}(B1 + f_r[\theta_0])^{\frac{4}{3}}} \right. \\ & \left. + \frac{8(A1 - (B1 + f_r[\theta_0])^{\frac{2}{3}})f_r'[\theta_0]^2}{9f_r[\theta_0]^{\frac{4}{3}}(B1 + f_r[\theta_0])^{\frac{1}{3}}} + \frac{4(A1 - (B1 + f_r[\theta_0])^{\frac{2}{3}})^2 f_r'[\theta_0]^2}{9f_r[\theta_0]^{\frac{2}{3}}} \right) \end{aligned}$$

$$(2.5) \quad \frac{4(A1 - (B1 + f_r[\theta_0])^{\frac{2}{3}}) f_r^{(2)}[\theta_0] (A1 - (B1 + f_r[\theta_0])^{\frac{2}{3}})^2 f_r^{(2)}[\theta_0]}{3 f_r[\theta_0]^{\frac{1}{3}} (B1 + f_r[\theta_0])^{\frac{1}{3}} \quad 3 f_r[\theta_0]^{\frac{4}{3}}}$$

$$\text{Where } A1 = p_r^{\frac{2}{3}} + \frac{2A}{3N p_r^{\frac{1}{3}}} - \frac{A^2}{9N^2 p_r^{\frac{4}{3}}} \quad B1 = \frac{B}{N}$$

2.1 MLE, MCSE and MBE of the parameter of Exponential distribution.
The probability density function of exponential random variable X with parameter θ is defined as:

$$f(x; \theta) = \frac{1}{\theta} e^{-x/\theta} \quad x \geq 0 \quad \theta > 0$$

And

$$f_r[\theta] = P(l_r < x < u_r) = \int_{l_r}^{u_r} \frac{e^{-x/\theta}}{\theta} dx \quad (2.1.1)$$

Where l_r and u_r are the lower and upper class boundaries respectively of r th cell. The class interval is determined by adjusting the extreme classes. The extreme classes are taken as $<c1\theta$ and $>c2\theta$ where $c1$ and $c2$ are some constants. The class interval is then $(c2-c1)\theta/(K-2)$. In this study the extreme classed are made with $c1=0.5$ and $c2=5.0$.
The first two derivations of (2.1.1) with respect to θ , are

$$f_r'[\theta] = \frac{e^{-l_r/\theta} l_r - e^{-u_r/\theta} u_r}{\theta^2}$$

$$f_r^{(2)}[\theta] = \frac{e^{-l_r/\theta} (l_r - 2\theta) l_r - e^{-u_r/\theta} (u_r - 2\theta) u_r}{\theta^4}$$

The MLE, MCSE and MBE of θ are obtained from (2.2), (2.3) and (2.5)

respectively with initial value $\theta_0 = \frac{\sum_{r=1}^K N_r m_r}{N}$ where m_r is the class mark of r th class.

3.1 Numerical Study

The study is based on the following choices of N-the sample size, NS-the number of samples and K-the number of classes.
N=20, 30, 50, 100, 500, 1000.

NS=25000, 50000, 100000 for $N < 100$, $N < 1000$ and $N = 1000$ respectively.

$K = 5, 10, 15$, and 20

In case of Exponential distribution random samples are generated through

$$x = -\theta \ln(1 - F(x))$$

Where $F(x)$ -the distribution function of exponential distribution is generated by subroutine ran2 of FORTRAN 7.

For each sample MLE, MCSE, and MBE are computed using (2.2), (2.3) and (2.5) respectively. Then, mean, absolute percent bias, variance, and mean square error of the estimates are obtained. Berkson (1980) calculates the efficiency using ratio of Mean Square Errors whereas Robert and Rao (1993) use ratio of variances. The efficiency of MBE over MLE and MCSE is calculated for both of these criteria.

Notations:

$$APBB = | \theta - E(\hat{\theta}_B) | / \theta \times 100 \quad MSEBM = MSE(\hat{\theta}_M) / MSE(\hat{\theta}_B) \times 100$$

$$VAREBM = VAR(\hat{\theta}_M) / VAR(\hat{\theta}_B) \times 100$$

$$APBC = | \theta - E(\hat{\theta}_C) | / \theta \times 100 \quad MSEBC = MSE(\hat{\theta}_C) / MSE(\hat{\theta}_B) \times 100$$

$$VAREBC = VAR(\hat{\theta}_C) / VAR(\hat{\theta}_B) \times 100$$

$$APBM = | \theta - E(\hat{\theta}_M) | / \theta \times 100 \quad MSEMCM = MSE(\hat{\theta}_C) / MSE(\hat{\theta}_M) \times 100$$

$$VAREMC = VAR(\hat{\theta}_C) / VAR(\hat{\theta}_M) \times 100$$

4. CONCLUSION

Table 3.1 gives the mean square error and variance efficiencies of MLE over MCSE together with absolute percent bias for few choices of θ . The study of the table reveals that what ever is the sample size or the number of cells (K), MLE is more efficient than MCSE whether we use MSE efficiency or variance efficiency. The absolute percent bias in MLE for small samples is also less than that of MCSE. Table 3.2 shows the relative efficiency of MBE over MLE and MCSE for $\theta = 0.5, 1.0, 2.0,$ and 5.0 together with the absolute percent bias. The study of the table concludes that for $A = 0.0$ and $B = 0.0$, MBE is slightly more efficient than MLE for small samples but it is far more efficient than MCSE.

Table 3.1 Relative Efficiency of MLE over MCSE extreme classes: ($< .5 \theta$), ($> 5.0 \theta$)

$\theta = .5 K = 5$					$\theta = 1.0 K = 5$				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	140.7	.64	9.42	122.5	20	133.8	.27	9.12	119.3
30	129.2	.95	7.95	113.5	30	134.3	.37	7.96	117.8
50	119.0	.52	4.72	109.5	50	122.0	.33	5.07	111.5
100	108.2	.31	2.68	101.5	100	110.0	.56	2.57	103.9
500	105.0	.13	.87	101.8	500	101.2	.17	.54	100.2
1000	101.8	.13	.27	101.3	1000	102.9	.05	.43	101.1

$\theta = 1.5 K = 5$					$\theta = 2.0 K = 5$				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	139.4	1.51	10.68	119.3	20	138.2	.71	9.41	122.4
30	130.4	.22	7.39	116.3	30	132.7	.00	7.42	118.4
50	125.0	.97	6.16	108.7	50	119.6	.32	5.37	107.2
100	112.1	.47	2.77	105.4	100	113.1	.46	2.77	106.4
500	104.0	.10	.64	102.2	500	103.4	.00	.76	101.0
1000	102.1	.05	.44	100.5	1000	100.5	.11	.28	100.0

$\theta = 5.0 K = 5$					$\theta = .5 K = 10$				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	138.5	.91	9.68	122.4	20	216.3	.11	18.43	142.1
30	130.1	.18	7.45	115.1	30	191.2	.73	15.26	125.9
50	121.3	.01	5.31	108.5	50	170.0	.14	10.72	115.6
100	114.1	.30	3.59	103.3	100	138.2	.40	5.96	104.6
500	104.1	.15	.89	100.7	500	119.3	.18	1.72	104.1
1000	101.9	.09	.47	100.1	1000	103.1	.12	.67	99.2

$\theta = 1.0 K = 10$					$\theta = 1.5 K = 10$				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	196.8	.86	17.92	138.0	20	221.4	.87	19.92	146.1
30	199.6	.57	16.12	129.6	30	189.1	.20	14.98	125.4
50	179.9	.16	11.05	117.4	50	181.6	1.20	11.87	116.2
100	143.8	.38	6.00	106.8	100	148.3	.32	6.18	112.0
500	111.5	.09	1.45	101.8	500	113.3	.03	1.45	103.0
1000	107.1	.02	.81	100.6	1000	107.8	.07	.86	100.8

$\theta = 2.0$ K = 10					$\theta = 5.0$ K = 10				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	219.1	.55	19.34	143.8	20	226.6	.89	19.53	151.5
30	193.4	.06	14.86	128.6	30	185.1	.43	14.70	125.7
50	178.9	.33	11.29	116.3	50	168.3	.16	11.02	111.1
100	148.2	.20	6.33	110.1	100	147.3	.35	6.80	104.3
500	111.1	.03	1.52	100.4	500	119.2	.21	1.73	103.8
1000	104.3	.10	.69	100.1	1000	107.9	.09	.90	99.8

Table 3.1 (Continued)

$\theta = .5$ K = 15					$\theta = 1.0$ K = 15				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	301.6	.09	25.25	163.2	20	276.1	.74	24.89	154.5
30	271.3	.77	21.56	141.5	30	271.5	.54	22.01	140.3
50	226.3	.14	14.99	116.1	50	251.0	.17	15.49	127.9
100	189.3	.37	9.00	114.3	100	200.3	.33	9.06	113.7
500	138.7	.17	2.49	105.7	500	126.6	.12	2.23	103.7
1000	112.9	.12	1.12	100.9	1000	115.5	.00	1.23	100.6

$\theta = 1.5$ K = 15					$\theta = 2.0$ K = 15				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	295.2	1.09	26.64	159.3	20	278.2	.50	25.47	153.9
30	272.0	.31	21.10	141.7	30	270.7	.06	20.84	142.6
50	250.5	1.11	16.52	121.1	50	249.9	.35	15.77	126.2
100	198.7	.30	9.15	117.3	100	192.8	.18	9.14	113.8
500	129.8	.02	2.28	104.0	500	125.6	.02	2.31	100.3
1000	116.7	.07	1.28	101.4	1000	113.2	.11	1.10	101.6

$\theta = 5.0$ K = 15					$\theta = .5$ K = 20				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	286.4	.30	25.68	159.4	20	387.7	.23	30.83	175.9
30	268.5	.40	20.74	138.8	30	348.3	.66	26.27	150.0
50	246.6	.09	15.88	123.4	50	299.0	.27	18.68	129.3
100	202.5	.33	9.79	113.3	100	259.1	.34	11.71	118.8
500	137.1	.19	2.55	106.1	500	160.0	.18	3.25	105.8
1000	117.8	.10	1.30	101.3	1000	120.6	.12	1.49	100.0

$\theta = 1.0$ K = 20					$\theta = 1.5$ K = 20				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	356.9	.53	30.61	170.3	20	372.5	1.24	32.34	169.9
30	350.4	.60	26.88	155.0	30	334.7	.21	25.58	151.7
50	305.8	.23	19.09	136.2	50	314.9	1.13	20.34	129.3
100	265.5	.34	11.64	116.8	100	266.2	.29	11.87	120.8
500	149.1	.12	3.02	105.2	500	151.5	.01	3.14	104.3
1000	125.8	.01	1.62	100.9	1000	129.0	.07	1.67	102.4

$\theta = 2.0$ K = 20					$\theta = 5.0$ K = 20				
N	MSEMC	APB(M)	APB(C)	VAREMC	N	MSEMC	APB(M)	APB(C)	VAREMC
20	376.6	.82	31.99	169.2	20	374.4	.95	31.50	178.3
30	350.5	.03	25.65	154.1	30	325.6	.49	25.11	149.9
50	338.1	.43	19.77	136.8	50	320.1	.07	19.58	132.3
100	251.0	.14	11.86	116.6	100	255.4	.32	12.19	116.7
500	149.7	.01	3.12	103.6	500	160.4	.19	3.31	104.6
1000	124.7	.10	1.51	102.1	1000	130.8	.10	1.74	100.5

Table: 3.2 Relative Efficiency of MBE over MLE and MCSE

extreme classes: ($< .5 \theta$), ($> 5.0 \theta$)										
$\theta = .5$ $K = 5$ $A = 0$ $B = 0$										
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC	
20	102.7	146.9	102.5	126.4	1.1	.4	9.9	143.0	123.3	
30	102.0	135.3	101.8	117.4	1.0	.4	8.1	132.6	115.4	
50	100.3	116.7	100.6	108.4	.5	1.0	4.6	116.3	107.7	
100	99.5	108.5	99.6	101.1	.2	.4	2.8	109.1	101.5	
500	99.3	104.6	99.2	101.1	.1	.1	.9	105.3	101.9	
1000	99.2	98.6	99.3	98.3	.1	.2	.3	99.4	99.0	

$\theta = 1.0$ $K = 5$ $A = 0$ $B = 0$										
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC	
20	102.7	145.5	102.5	127.0	1.3	.6	10.1	141.6	123.9	
30	102.0	135.7	101.9	119.2	.4	.1	7.7	133.1	117.0	
50	100.9	121.7	101.1	110.3	.4	.8	5.0	120.6	109.0	
100	99.6	110.0	99.8	103.5	.3	.5	2.8	110.5	103.8	
500	100.0	100.3	100.0	99.2	.2	.2	.5	100.3	99.2	
1000	100.6	104.1	100.7	102.1	.1	.1	.5	103.4	101.4	

$\theta = 2.0$ $K = 5$ $A = 0$ $B = 0$										
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC	
20	102.7	145.3	102.4	126.1	1.5	.7	10.0	141.5	123.1	
30	102.0	135.1	101.8	116.2	.8	.3	8.3	132.4	114.1	
50	100.9	121.3	100.9	109.5	.2	.2	5.3	120.2	108.5	
100	99.3	109.9	99.6	104.3	.6	.8	2.6	110.7	104.7	
500	99.8	103.4	99.8	100.9	.0	.0	.8	103.6	101.0	
1000	100.2	100.7	100.3	100.0	.1	.1	.3	100.6	99.7	

$\theta = .5$ $K = 10$ $A = 0$ $B = 0$										
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC	
20	104.7	229.7	104.8	148.5	.3	.8	19.0	219.4	141.6	
30	104.1	196.8	104.0	128.2	.7	.2	15.6	188.9	123.2	
50	101.7	171.4	102.4	118.6	.5	1.2	10.2	168.5	115.8	
100	99.9	146.1	100.3	107.5	.2	.7	6.3	146.2	107.1	
500	99.6	118.2	99.6	103.9	.2	.2	1.7	118.7	104.3	
1000	100.2	105.5	100.2	101.7	.1	.1	.7	105.3	101.5	

$\theta = 1.0 \quad K = 10 \quad A = 0 \quad B = 0$									
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC
20	104.6	225.7	104.5	148.7	.7	.4	19.9	215.9	142.3
30	103.7	200.6	103.9	131.6	.1	.9	15.3	193.5	126.6
50	101.9	181.9	102.5	120.4	.2	1.0	11.0	178.5	117.5
100	99.9	146.9	100.3	108.0	.2	.7	6.2	147.0	107.6
500	99.5	109.3	99.6	100.4	.1	.1	1.4	109.8	100.8
1000	99.9	108.0	99.9	101.8	.0	.0	.8	108.1	101.8

Table: 3.2 (Continued)

$\theta = 2.0 \quad K = 10 \quad A = 0 \quad B = 0$									
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC
20	105.0	238.1	104.5	151.0	1.5	.4	20.6	226.8	144.4
30	103.4	199.6	103.5	132.8	.2	.8	15.1	193.2	128.3
50	102.8	185.0	102.9	122.5	.4	.4	11.3	179.9	119.1
100	100.4	147.9	101.0	110.4	.3	.8	6.3	147.3	109.3
500	99.6	110.7	99.6	100.5	.0	.0	1.5	111.1	100.9
1000	99.9	106.1	99.9	101.6	.1	.1	.7	106.2	101.8

$\theta = 5.0 \quad K = 10 \quad A = 0 \quad B = 0$									
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC
20	103.9	211.3	104.4	147.3	.6	1.6	18.0	203.3	141.1
30	103.3	190.4	103.9	129.5	.7	1.6	14.5	184.3	124.6
50	102.2	182.3	102.2	117.9	.4	.4	11.3	178.4	115.3
100	100.0	146.0	100.0	103.8	.3	.2	6.7	146.0	103.7
500	99.7	119.5	99.8	103.5	.2	.2	1.8	119.9	103.7
1000	99.9	107.7	99.9	100.1	.1	.1	.9	107.8	100.2

$\theta = .5 \quad K = 15 \quad A = 0 \quad B = 0$									
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC
20	104.3	317.2	104.5	168.8	.1	1.0	25.8	304.2	161.6
30	105.2	272.9	105.1	140.2	.7	.4	21.7	259.4	133.4
50	102.8	231.5	103.8	122.3	.6	1.5	14.5	225.2	117.8
100	100.5	201.0	101.2	114.0	.2	.8	9.2	199.9	112.6
500	99.4	135.8	99.4	104.9	.2	.1	2.5	136.6	105.6
1000	99.8	112.8	100.1	101.6	.1	.1	1.1	113.0	101.5

$\theta = 1.0$ K = 15 A = 0 B = 0										
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)			
MSEMC	VAREMC									
20	104.9	290.3	105.0	156.7	.4	.6	27.0	276.6	149.3	
30	105.2	285.8	105.6	150.7	.1	1.1	21.2	271.7	142.7	
50	103.5	255.6	104.2	130.9	.2	1.1	15.6	246.9	125.6	
100	100.3	207.2	101.1	116.2	.2	.9	9.3	206.5	115.0	
500	99.3	122.6	99.4	101.7	.1	.2	2.2	123.5	102.3	
1000	99.8	115.8	99.8	101.5	.0	.0	1.2	116.1	101.7	

$\theta = 2.0$ K = 15 A = 0 B = 0										
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)			
MSEMC	VAREMC									
20	105.0	302.5	104.6	160.7	1.5	.4	27.1	288.1	153.6	
30	104.6	288.4	104.9	148.7	.1	1.0	21.6	275.7	141.8	
50	103.7	251.1	103.7	131.4	.4	.6	15.6	242.2	126.6	
100	101.1	192.7	102.0	111.9	.3	1.0	9.1	190.7	109.7	
500	99.1	123.0	99.1	98.6	.0	.1	2.3	124.2	99.5	
1000	99.9	113.8	99.9	102.2	.1	.1	1.1	113.9	102.2	

Table: 3.3 (Continued)

$\theta = 5.0$ K = 15 A = 0 B = 0										
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)			
MSEMC	VAREMC									
20	104.0	291.0	104.6	163.9	.9	1.8	24.9	279.7	156.7	
30	104.4	270.6	105.1	142.7	.6	1.5	20.8	259.1	135.7	
50	103.2	261.1	103.4	131.6	.2	.7	15.9	253.1	127.3	
100	100.6	200.0	100.8	110.0	.3	.4	9.7	198.7	109.2	
500	99.6	137.4	99.4	103.1	.2	.1	2.5	137.9	103.7	
1000	99.8	117.7	99.6	100.5	.1	.1	1.3	117.9	100.8	

$\theta = .5$ K = 20 A = 0 B = 0										
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)			
MSEMC	VAREMC									
20	104.1	407.7	104.1	181.9	.4	.5	31.4	391.8	174.8	
30	105.1	364.9	104.9	155.4	.9	.1	26.8	347.2	148.2	
50	103.9	311.1	105.2	133.8	.6	1.6	18.3	299.5	127.2	
100	101.0	270.7	101.9	122.7	.2	.9	12.0	268.0	120.4	
500	99.4	157.6	99.4	105.2	.2	.0	3.3	158.5	105.9	
1000	99.3	120.6	99.4	99.3	.1	.1	1.5	121.5	99.9	

$\theta = 1.0$ K = 20 A = 0 B = 0									
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC
20	104.4	363.8	104.4	172.2	.1	.5	32.3	348.5	164.9
30	105.4	364.7	105.6	160.6	.2	.7	26.5	346.0	152.2
50	104.0	330.7	104.9	142.7	.4	1.4	19.2	318.1	136.0
100	101.4	266.1	102.3	121.3	.1	.9	11.9	262.5	118.7
500	99.0	145.7	99.4	103.5	.2	.3	3.0	147.1	104.2
1000	99.6	126.5	99.7	100.6	.0	.0	1.6	127.0	100.9

$\theta = 2.0$ K = 20 A = 0 B = 0									
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC
20	104.0	387.7	103.7	175.2	1.4	.6	33.0	372.7	169.0
30	104.4	355.9	104.7	158.7	.0	1.0	25.8	340.9	151.5
50	104.4	325.8	104.4	137.4	.5	.6	19.5	312.2	131.6
100	101.6	260.2	102.8	121.3	.3	1.1	11.8	256.2	118.1
500	99.2	149.8	99.3	103.1	.0	.1	3.1	151.0	103.8
1000	99.8	124.4	99.8	102.3	.1	.1	1.5	124.7	102.5

$\theta = 5.0$ K = 20 A = 0 B = 0									
N	MSEBM	MSEBC	VAREBM	VAREBC	APB(M)	APB(B)	APB(C)	MSEMC	VAREMC
20	104.0	381.1	104.3	176.7	.5	1.2	30.9	366.4	169.5
30	104.5	341.3	105.1	157.5	.6	1.5	25.2	326.5	149.8
50	103.7	342.1	104.0	140.1	.3	.8	19.6	329.7	134.7
100	101.6	258.0	101.9	117.8	.2	.6	12.2	253.8	115.6
500	99.5	157.2	99.3	103.3	.2	.1	3.3	158.0	104.0
1000	99.7	133.5	99.4	102.9	.1	.1	1.7	133.9	103.6

REFERENCE

1. Berkson, J (1980). Minimum chi-square, not maximum likelihood. Annals of Statistics, 8, 457 —.
2. Fisher, R.A (1922). On the interpretation of X^2 from contingency tables, and the calculation of P. J. Roy. Statist. Soc. , 58, 87- .
3. Khan, M. A and Baily, B. J. R (1987). A new test statistic of goodness of fit. Pak. J. Statist., 3, 135 —.
4. Khan, M. A (1988). Small sample distribution of Minimum - B estimate. Pak. J. Statist., 4, 1 —.
5. Rao, C. R. (1962). Efficient estimates and optimum inference procedures in large samples. JRSS., 24B, 46 —.
6. Robert, L. Fountain and Rao, C. R (1993). Further investigations of Berkson's example. Commun. Statist., Theory Meth., 22(3), 613