

COMPARISON OF ESTIMATORS FOR THE PARAMETERS OF THE
POISSON-GAMMA MARGINAL DISTRIBUTION

by

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A MASTER'S REPORT

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requirements for the degree

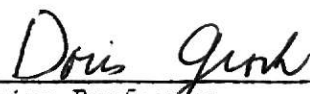
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This Report is dedicated to my parents, who taught me the
important things.

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**THIS BOOK
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SECTION 1: DERIVATIONS

Consider a Poisson process arising from an experiment where a component is observed for time T . During the duration of the experiment let X denote the number of "arrivals" (equipment failures and instantaneous repairs). Since this is a Poisson process, we assume an unknown arrival rate λ . The probability function for $X = x$ is

$$[1.1] \quad f(X|\lambda, T) = \frac{e^{-\lambda T} (\lambda T)^x}{x!} \quad \begin{matrix} I(x) \\ \{0, 1, 2, \dots\} \end{matrix}$$

with $E(X|\lambda, T) = \lambda T$

and $\text{Var}(X|\lambda, T) = \lambda T$.

Using classical analysis the method of moments estimator of λ (also maximum likelihood estimator) is $\lambda = \frac{X}{T}$.

Thinking of λ in the Bayesian sense implies that the particular failure rate for an experiment is a realization of Λ , a random variable with some distribution, $g(\lambda|\theta)$. In this way we say that λ , the arrival rate of the Poisson process, is not a fixed value for every experiment; instead it may vary. In choosing a prior distribution $g(\lambda|\theta)$ it is important to choose one which gives positive probability to all possible values of λ and zero probability to those values not feasible. It is important to choose a distribution with flexible shape and one which is mathematically conformable to the conditional distribution $f(x|\lambda, T)$. For this case the gamma distribution fulfills all these requirements.

Assuming $\Lambda \sim \text{gamma}(\alpha, \beta)$ gives probability density function

$$[1.2] \quad g(\lambda|\alpha, \beta) = \frac{\lambda^{\alpha-1}}{\Gamma(\alpha)\beta^\alpha} e^{-\frac{\lambda}{\beta}} \quad \begin{matrix} I(\lambda) \\ [0, \infty) \end{matrix}$$

This distribution has as its support the interval $[0, \infty)$. Note that for all

values of α and β $\lim_{\lambda \rightarrow \infty} (g(\lambda|\alpha, \beta)) = 0$. However, the shape of the distribution varies widely according to α . The parameter β is a scale parameter, thus providing sufficient flexibility of shape and scale.

Having assumed a gamma (α, β) prior distribution for λ it is necessary to know the particular distribution from which the λ is drawn. In other words, estimates of α and β are needed. The actual λ from each experiment is never observed, but is estimated by $\frac{x}{T}$. The estimates of α and β then will be based on the estimates of λ .

Recall we have conditional distribution

$$[1.1] \quad f(x|\lambda, T) = \frac{e^{-\lambda T} (\lambda T)^x}{x!} I(x) \quad \{0, 1, 2, \dots\}$$

and prior distribution

$$[1.2] \quad g(\lambda|\alpha, \beta) = \frac{\lambda^{\alpha-1}}{\Gamma(\alpha) \beta^\alpha} e^{-\frac{\lambda}{\beta}} I(\lambda) \quad [0, \infty)$$

This gives a marginal distribution of X free of

$$h(x|\alpha, \beta) = \int_0^\infty \frac{e^{-\lambda T} (\lambda T)^x}{x!} \frac{\lambda^{\alpha-1} e^{-\frac{\lambda}{\beta}}}{\Gamma(\alpha) \beta^\alpha} d\lambda = \frac{T^x \Gamma(\alpha+x)}{\Gamma(\alpha) x! \beta^\alpha (T+\frac{1}{\beta})^{\alpha+x}}$$

Now let $\frac{1}{\beta} = T'$.

$$[1.3] \quad h(x|\alpha, \beta) = \binom{\alpha+x-1}{\alpha} \left(\frac{T'}{T+T'}\right)^\alpha \left(\frac{T}{T+T'}\right)^x I(x) \quad [0, 1, 2, \dots]$$

For integer α this is the negative binomial distribution with $x+\alpha$ trials until α successes, with probability of success $p = T/(T+T')$. This has

$$E(X) = \alpha \left(\frac{T}{T+T'} \right) \left(\frac{T+T'}{T'} \right) = \alpha \beta T$$

and

$$\begin{aligned} \text{Var}(X) &= \alpha \left(\frac{T}{T+T'} \right) \left(\frac{T+T'}{T'} \right)^2 \\ &= \alpha \beta^2 T (T+T') \\ &= \alpha \beta^2 T^2 + \alpha \beta T \end{aligned}$$

$$\text{Then } E(\hat{\lambda}) = E\left(\frac{X}{T}\right) = \alpha \beta$$

$$\text{and } \text{Var}(\hat{\lambda}) = \text{Var}\left(\frac{X}{T}\right) = \frac{\alpha \beta}{T} + \alpha \beta^2$$

The $\hat{\lambda}$ is observable while λ is not. For this reason all estimation will be done from the marginal distribution and not the prior distribution.

The posterior distribution is

$$[1.4] \quad k(\lambda | x, T) = \frac{e^{-\lambda(T+\frac{1}{\beta})} \lambda^{\alpha+x-1} (T+\frac{1}{\beta})^{\alpha+x}}{\Gamma(\alpha+x)} \quad \begin{matrix} I(\lambda) \\ [0, \infty) \end{matrix}$$

This is a gamma($\alpha+x, (T'+T)^{-1}$) distribution where $T' = \frac{1}{\beta}$. It will be helpful to keep this in mind when interpreting α and β . We define x to be the number of arrivals and we can think of α as a "pseudo" number of arrivals. T is the experiment time and $T' = \frac{1}{\beta}$ is a "pseudo" experiment time.

The experiment is repeated n times resulting in a collection of times $T_1, \dots, T_n$ and arrival counts $x_1, \dots, x_n$. This gives n estimates $\hat{\lambda}_1, \dots, \hat{\lambda}_n$. From these $\hat{\lambda}_1$ four methods of estimating α and β will be discussed. The first two estimators are method-of-moments estimators, the third is a maximum likelihood estimator and the fourth matches moments to the prior distribution.

SECTION 2: ESTIMATORS

2.1 Unweighted Method-of-Moments Estimation

In this case all experiments are considered equally informative and a λ_i from a short duration experiment is considered as important as one from a long duration experiment. The unweighted average is defined as

$$[2.1.1] \quad \bar{\lambda}_u = \frac{1}{n} \sum_{i=1}^n \hat{\lambda}_i$$

and the unweighted variance as

$$[2.1.2] \quad S_{\lambda_u}^2 = \frac{1}{n-1} \sum_{i=1}^n (\hat{\lambda}_i - \bar{\lambda}_u)^2$$

Note that

$$E(\bar{\lambda}_u) = \frac{1}{n} E \sum_{i=1}^n (\hat{\lambda}_i) = \alpha\beta$$

and

$$E(S_{\lambda_u}^2) = \frac{1}{n-1} E \sum_{i=1}^n (\hat{\lambda}_i - \bar{\lambda}_u)^2 = \frac{1}{n-1} E(U)$$

where, using matrix notation for convenience,

$$U = \hat{\lambda}' (I - \frac{1}{n} J) \hat{\lambda} \quad \text{and} \quad \hat{\lambda} = (\hat{\lambda}_1, \dots, \hat{\lambda}_n)$$

I is the nxn identity and J is an nxn matrix of ones. From linear model theory

$$E(\hat{\lambda}' (I - \frac{1}{n} J) \hat{\lambda}) = E(\hat{\lambda}' A \hat{\lambda}) = \text{tr}(A \Phi) + \text{tr}(A \underline{\mu} \underline{\mu}') \quad (2.1.3)$$

where Φ is the variance-covariance matrix of $\hat{\lambda}$ and $\underline{\mu}$ is the mean of $\hat{\lambda}$. Here

$\underline{\mu}' = \alpha\beta(1\dots 1)$ and $\dagger = [V_{ij}]_{n \times n}$, with

$$V_{ij} = 0, \quad i \neq j$$

$$V_{ij} = \alpha\beta^2 + \frac{\alpha\beta}{T_i}, \quad i=j.$$

$\dagger$ is a diagonal matrix since each experiment is independent of any other.

Therefore

$$E(\hat{\underline{\lambda}}' (I - \frac{1}{n}J) \hat{\underline{\lambda}}) = (n-1)(\alpha\beta^2 + \frac{\alpha\beta}{n} \sum \frac{1}{T_i}).$$

Hence

$$E(S_{\lambda_u}^2) = \alpha\beta^2 + \frac{n\alpha\beta}{\sum T_i}.$$

Hence we have

$$E(\bar{\lambda}_u) = \alpha\beta$$

and

$$E(S_{\lambda_u}^2) = \alpha\beta^2 + \frac{n\alpha\beta}{\sum_{i=1}^n T_i}$$

The unweighted method-of-moments estimators of α and β are

$$\hat{\alpha}_u = \frac{\bar{\lambda}_u^2}{S_{\lambda_u}^2 - \frac{n\bar{\lambda}_u}{\sum_{i=1}^n \frac{1}{T_i}}}$$

and

$$\hat{\beta}_u = \frac{S_{\lambda_u}^2}{\bar{\lambda}_u} - \frac{n}{\sum_{i=1}^n \frac{1}{T_i}}$$

2.2 Time-Weighted Method-of-Moments Estimation

It can be argued that those experiments with long duration provide more information than those which are short. Hence the concept of time-weighting arises. Define the time-weighted mean as

$$[2.2.1] \quad \bar{\lambda}_T = \frac{\sum_{i=1}^n T_i \hat{\lambda}_i}{\sum_{i=1}^n T_i} = \frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n T_i}$$

and the time-weighted variance as

$$[2.2.2] \quad S_{\lambda_T}^2 = \frac{\sum_{i=1}^n T_i (\hat{\lambda}_i - \bar{\lambda}_T)^2}{\sum_{i=1}^n T_i}.$$

Note that $E(\bar{\lambda}_T) = \alpha\beta$.

We can then express the observed $\hat{\lambda}_i$ in terms of the linear model

$$\underline{\hat{\lambda}} = \underline{j}(\alpha\beta) + \underline{\varepsilon}$$

where $\underline{\hat{\lambda}} = (\hat{\lambda}_1, \dots, \hat{\lambda}_n)$, $E(\hat{\lambda}_i) = \alpha\beta$, and $E(\underline{\varepsilon}) = \underline{0}$ with $\text{Var}(\underline{\varepsilon}) = \underline{\Phi} = \text{diag}(\alpha\beta^2 + \frac{\alpha\beta}{T_i})$.

Let $T = \text{diag}(T_i)$ then

$$T^2 \underline{\hat{\lambda}} = T^2 \underline{j}(\alpha\beta) + (\underline{\varepsilon}')$$

The BLUE of $\alpha\beta$ then is

$$\hat{\alpha\beta} = (\underline{j}' T \underline{j})^{-1} \underline{j}' T \underline{\hat{\lambda}} = \frac{\sum_{i=1}^n T_i \hat{\lambda}_i}{\sum_{i=1}^n T_i} = \bar{\lambda}_T$$

and the residual sum of squares is

$$\begin{aligned} & \hat{\lambda}' \underline{T}^{\frac{1}{2}} (\underline{I} - \underline{T} \underline{j} (\underline{j}' \underline{T} \underline{j})^{-1} \underline{j}' \underline{T}^{\frac{1}{2}}) \underline{T}^{\frac{1}{2}} \hat{\lambda} \\ &= \hat{\lambda}' \left(\underline{T} - \frac{\underline{T} \underline{j} \underline{j}' \underline{T}}{\sum_{i=1}^n T_i} \right) \hat{\lambda} = \sum_{i=1}^n T_i (\hat{\lambda}_i - \bar{\lambda}_T)^2 \end{aligned}$$

Let
$$\underline{U} = \left(\underline{T} - \frac{\underline{T} \underline{j} \underline{j}' \underline{T}}{\sum_{i=1}^n T_i} \right)$$

then

$$E(\hat{\lambda}' \underline{U} \hat{\lambda}) = \sum_{i=1}^n T_i E(\hat{\lambda}_T^2) = \text{tr}(\underline{U} \underline{\Phi}) + \underline{\mu}' \underline{U} \underline{\mu}$$

where $\underline{\Phi} = \text{Var}(\hat{\lambda}) = \text{diag}(\alpha\beta^2 + \frac{\alpha\beta}{T_i}) = \alpha\beta^2 \underline{I} + \alpha\beta \underline{T}^{-1}$ and $\underline{\mu} = E(\hat{\lambda}) = \underline{j}(\alpha\beta)$.

$$\text{tr}(\underline{U} \underline{\Phi}) + \underline{\xi}' \underline{U} \underline{\xi} = \alpha\beta^2 \sum_{i=1}^n T_i - \alpha\beta^2 \frac{\sum_{i=1}^n T_i^2}{\sum_{i=1}^n T_i} + (n-1)\alpha\beta$$

Then

$$E(\hat{\lambda}_T^2) = \alpha\beta^2 \left(1 - \frac{\sum T_i^2}{(\sum T_i)^2} \right) + \frac{n-1}{T_i} \alpha\beta$$

The time-weighted method of moments estimators are

$$\hat{\alpha}_T = \frac{\bar{\lambda}_T^2 \left[1 - \frac{\sum_{i=1}^n T_i^2}{(\sum_{i=1}^n T_i)^2} \right]}{S_{\lambda_T}^2 - \frac{(n-1)\bar{\lambda}_T^2}{\sum_{i=1}^n T_i}}$$

and

$$\hat{\beta}_T = \frac{\bar{\lambda}_T}{\hat{\alpha}_T}$$

These estimators differ from the unweighted method-of-moments estimators by a factor of

$$\left(1 - \frac{\sum_{i=1}^n T_i^2}{\left(\sum_{i=1}^n T_i\right)^2}\right)$$

and n is replaced by $n-1$. Note that if $T_i = T_j$, $\forall i, j = 1, \dots, n$

$$\frac{\sum_{i=1}^n T_i^2}{\left(\sum_{i=1}^n T_i\right)^2} = \frac{1}{n}$$

and the time-weighted and unweighted method of moments estimators are identical.

2.3 Maximum Likelihood Estimation

Since the λ_i 's are never observed, rather they are only estimated, the marginal distribution is used. Recall from equation [1.3] that the marginal distribution is negative binomial and can be written as

$$h(x|\alpha, \beta) = \frac{\beta^x T^x \Gamma(x+\alpha)}{\Gamma(\alpha) x! (1+\beta T)^{x+\alpha}}$$

The likelihood function is

$$[2.3.1] \quad L = \prod_{i=1}^n \frac{T_i^{x_i} \beta^{x_i} \Gamma(x_i + \alpha)}{\Gamma(\alpha) x_i! (1 + \beta T_i)^{x_i + \alpha}}$$

Let

$$K_i = \frac{T_i^{x_i}}{x_i!}$$

$$L = \prod_{i=1}^n \frac{K_i \beta^{x_i} \Gamma(x_i + \alpha)}{\Gamma(\alpha) (1 + \beta T_i)^{x_i + \alpha}}$$

Then the log-likelihood function is

$$\mathcal{L} = \sum_{i=1}^n \left[(\ln K_i + x_i \ln \beta + \ln \left(\frac{\Gamma(x_i + \alpha)}{\Gamma(\alpha)} \right) - (x_i + \alpha) \ln(1 + \beta T_i)) \right]$$

Note that

$$\ln \left(\frac{\Gamma(x_i + \alpha)}{\Gamma(\alpha)} \right) = \ln \left(\frac{(x_i + \alpha - 1) \dots (\alpha + 1) \alpha \Gamma(\alpha)}{\Gamma(\alpha)} \right) = \sum_{z=1}^{x_i} \ln(\alpha - 1 + z)$$

so that

$$[2.3.2] \quad \mathcal{L} = \sum_{i=1}^n \ln K_i + \ln \beta \sum_{i=1}^n x_i + \sum_{i=1}^n \sum_{z=1}^{x_i} \ln(\alpha + z - 1) - \sum_{i=1}^n (x_i + \alpha) \ln(1 + \beta T_i)$$

The likelihood equations are

$$[2.3.3] \quad f = \frac{\partial \mathcal{L}}{\partial \alpha} = \sum_{i=1}^n \sum_{z=1}^{x_i} \frac{1}{(\alpha + z - 1)} - \sum_{i=1}^n \ln(1 + \beta T_i)$$

and

$$[2.3.4] \quad g = \frac{\partial \mathcal{L}}{\partial \beta} = \frac{\sum_{i=1}^n x_i}{\beta} - \sum_{i=1}^n \frac{(x_i + \alpha) T_i}{1 + \beta T_i}$$

No simple closed form solutions for $\hat{\alpha}$ and $\hat{\beta}$ can be found by setting the likelihood equations to zero, hence the Newton-Raphson iterative procedure is used to solve for the estimates. The Newton-Raphson procedure is derived and detailed in Section 5: Documentation.

2.4 Matching-Moments-to-the-Prior Estimation

As a point of interest the estimators

$$\hat{\alpha}_c = \frac{\bar{\lambda}^2}{S_{\lambda_u}^2}$$

and

$$\hat{\beta}_c = \frac{S_{\lambda_u}^2}{\bar{\lambda}_u}$$

are investigated. Recall the prior distribution of lambda is $\Lambda \sim \text{gamma}(\alpha, \beta)$ which has classical method of moments estimators

$$[2.4.1] \quad \hat{\alpha} = \frac{\bar{\lambda}^2}{S^2} \quad \text{and} \quad \hat{\beta} = \frac{S^2}{\bar{\lambda}}$$

[2.4.2]

The unweighted and time-weighted method-of-moments estimators reduce to the matching-moments-to-the-prior estimators under special conditions. The two types of method-of-moments estimators are identical for equal experiment times. Consider the estimators if each experiment is continued infinitely long, that is, if for fixed n , it is true that

$$\sum_{i=1}^n T_i = \infty.$$

Then

$$\hat{\alpha} = \frac{\bar{\lambda}^2}{S^2 \frac{n \hat{\lambda}}{\sum_{i=1}^n T_i}} \rightarrow \frac{\bar{\lambda}^2}{S^2}$$

and

$$\hat{\beta} = \frac{S^2}{\hat{\lambda}} - \frac{n}{\sum_{i=1}^n T_i} \rightarrow \frac{S^2}{\hat{\lambda}} \text{ as } \sum_{i=1}^n T_i \rightarrow \infty .$$

This is consistent with the assumption of using the prior distribution, since if each experiment is continued infinitely long, the true arrival rate λ is observed.

These matching moments-to-the-prior estimators are not successful estimators of α and β , but they are useful as starting values in the Newton-Raphson procedure for finding the maximum likelihood estimators.

As sample size increases, that is, more experiments are used in averaging, the means of the matching-moments-to-the-prior estimators drift steadily away from the true value of the parameters being estimated. This result supports the use of the marginal distribution by emphasizing the fact that values from the prior distribution are not observed. These results became apparent early in this study and hence the matching moments with the prior estimators are not discussed further.

SECTION 3: BACKGROUND AND OBJECTIVES

Work on this problem began when the Nuclear Regulatory Commission provided data consisting of failure data on various types of pumps. Since the experiments were conducted on a number of days under various conditions and involved machines produced by different manufacturers it was reasonable to assume that the Poisson parameter λ was not fixed but for each experiment λ was a value of Λ , a random variable with distribution, in this case, $\text{gamma}(\alpha, \beta)$. The λ from the i^{th} experiment was never observed, so that the prior distribution is not available. The values which are observable are the estimates of λ , that is $\hat{\lambda} = \frac{x}{T}$. In order to use this available information to estimate the parameters of the gamma distribution the marginal distribution is used. We have no observations from the gamma prior distribution but each experiment gives an observation from the marginal distribution which, as shown in Section 1: Derivation, is the negative binomial distribution.

Values of α and β were selected and fixed for the simulation. The values chosen were $\alpha = 2$ and $\beta = \frac{1}{T_i} = .001$. Original plans included other values of α and β but the cost of further experimentation was prohibitive. With this in mind the resulting marginal distribution is

$$h(x|\alpha, \beta) = \binom{x_i + 2 - 1}{2} \left(\frac{1000}{T_i + 1000} \right)^2 \left(\frac{T_i}{T_i + 1000} \right)^{x_i}.$$

For the purpose of simulating, experiment times T_i were generated randomly for Population One from a discrete uniform (0,9999) distribution by taking a random number in the interval (0,1), multiplying by 10,000 and retaining the integer part of the product. Upon visual examination these values of T_i did not "look" as widely spread as those observed in the Nuclear Regulatory

Commission data. Therefore another randomization is induced in Population Two. The multiplier is determined by another random number, RM, such that

$$\text{Multiplier} = \begin{cases} 1,000 & \text{if } RM < .3 \\ 10,000 & \text{if } .3 \leq RM \leq .7 \\ 100,000 & \text{if } .7 < RM \end{cases}$$

where $RM \sim \text{uniform}(0,1)$. This second randomization provides $0 < T_i < 100,000$. T_i is no longer from a uniform distribution. This is the sole difference between the generation of the two populations. The results obtained from the two populations vary in several ways as described below.

After the random experiment time is determined, a probability of a success in the marginal negative binomial distribution was calculated,

$$P_i = \frac{T'}{T_i + T'} = \frac{1000}{T_i + 1000}.$$

Another random number, R, was generated and compared with P. If $R \leq P$, then it was deemed to be a success and if $R > P$ it was called a failure. The distribution gives the probability of x_i failures until the α^{th} success. Therefore $\alpha = 2 = \text{total successes}$ and $x_i = \text{total failures}$. For each single experiment we have α "pseudo arrivals" in "pseudo experiment time" $T' = \frac{1}{\beta}$, and a simulated x_i arrivals in experiment time T_i .

From this information the estimate $\hat{\lambda}_i = \frac{x_i}{T_i}$ was computed. A sample of size ten consisted of ten single experiments and resulted in ten estimates $\hat{\lambda}_i$. Likewise for samples of size 20, 30, 40, ..., 100. The 10(20, 30, ..., 100) estimates $\hat{\lambda}_i$ were combined according to either the unweighted or the time-weighted methods described in subsections 2.1 and 2.2. These were the values used in the estimates of α and β as prescribed for the various estimators. Five hundred estimates of α and β of each type of estimator were generated for each sample size.

It was observed when working with small contrived samples (used to verify by hand calculation a computer program that was under development) that the unweighted and time-weighted method-of-moments estimates obtained were sometimes negative in value. Thus arose the first objective of this report. It was desired to determine if the method-of-moments estimates do, in real life situations, take on negative values, and if so, how often this occurs. Lacking a large body of real data, the method of simulation was selected to observe in a more realistic situation the values which might be obtained. The second objective of this report was to determine from the simulation some of the major characteristics of the empirical distributions of the unweighted and time-weighted method-of-moments estimators and the maximum likelihood estimators, and to compare various aspects of the estimators.

SECTION 4: RESULTS

Many interesting and unexpected results of the simulation were observed. Figures 4.1.1 to 4.1.6 are histograms of the unweighted method-of-moments estimates from Population One and Two and samples of size 10, 50 and 100. Figures 4.2.1 to 4.2.6 and Figures 4.3.1 to 4.3.6 are histograms of the time-weighted method-of-moments estimates and the maximum likelihood estimates from the same samples. It is easily noted that the estimates from Population Two with the wide spread experiment times display much more erratic behavior than those from Population One with experiment times from a uniform distribution. We now compare the advantages and disadvantages of the estimators.

4.1 Unweighted Method-of-Moments Estimators

It was noted that the unweighted method-of-moments estimates were often negative in value. As many as 41 percent of the 500 samples of size 100 from Population Two gave negative results. In general the number of negative values decreased as the sample size increased. The first 50 samples of size 10 are displayed in Table 4.1.1. These are included to give the reader a feel for the type of data generated by the simulation. Table 4.1.1a shows the samples from Population One and Table 4.1.1b shows the samples from Population Two. No readily apparent difference was discerned between samples which produced negative estimates and those which produced positive estimates. Noticably fewer negative estimates arose from Population One than from Population Two, indicating that a larger variance among the experiment times might contribute to a negative value of the unweighted method-of-moments estimate. A spot check of samples in Table 4.1.1 did not support this conclusion.

The ranges of values for $\hat{\alpha}_u$ and $\hat{\beta}_u$ decrease in Population One as the sample size increases. This pattern is repeated for $\hat{\beta}_u$ in Population Two

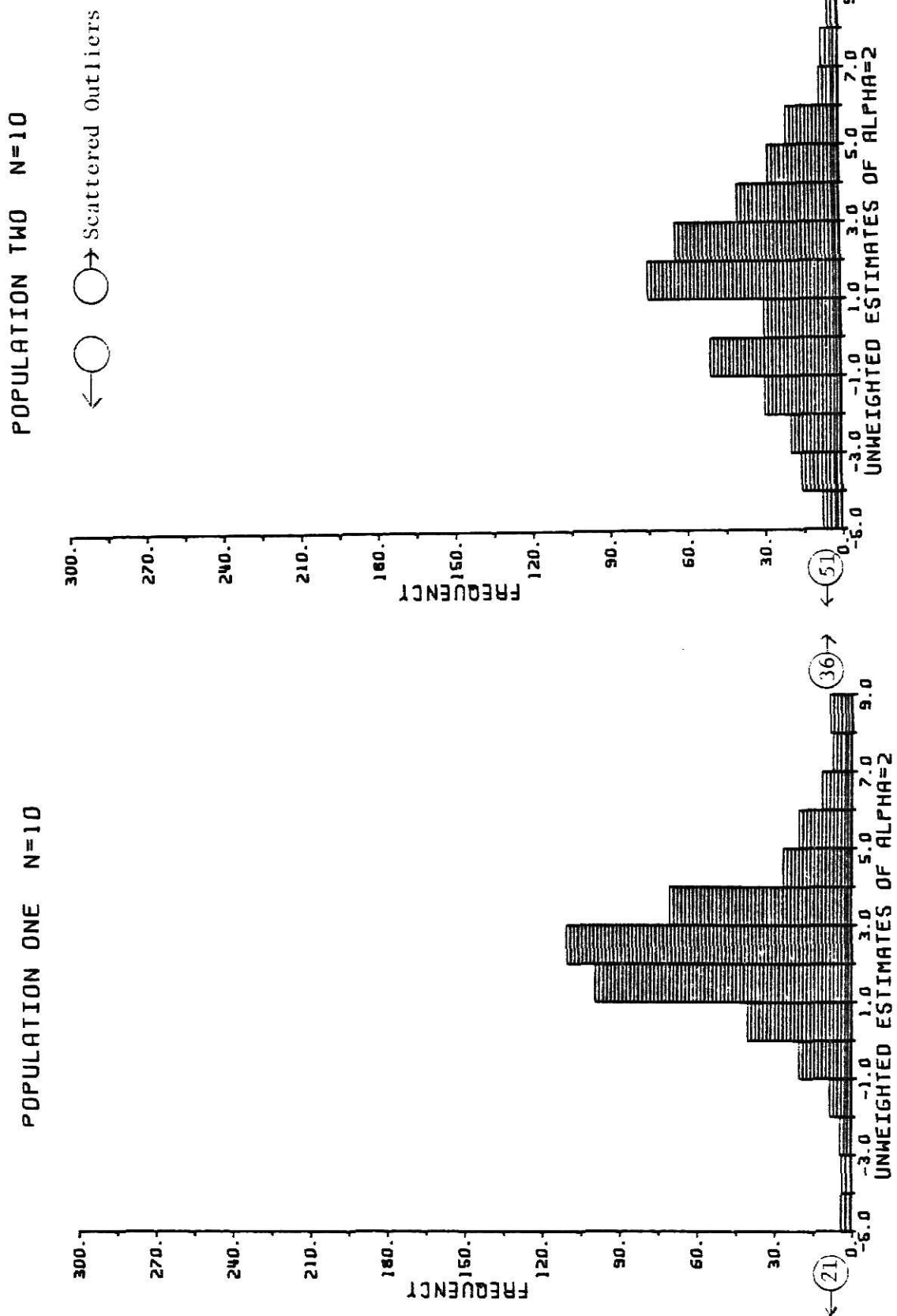
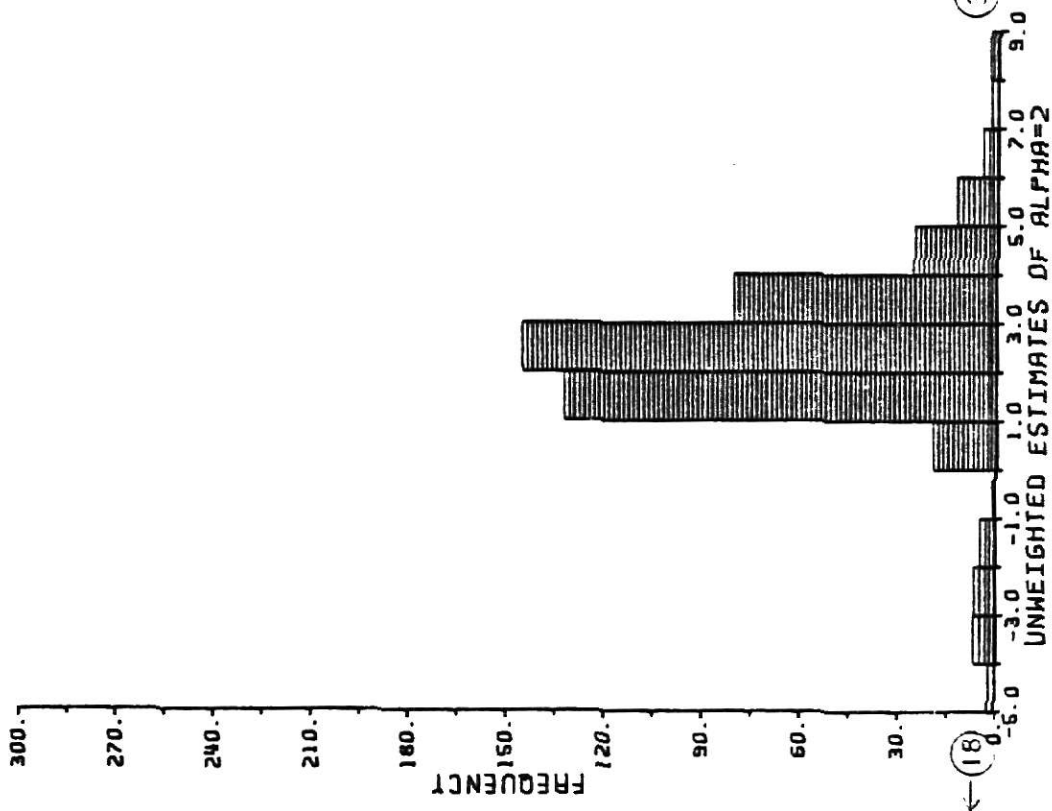


Figure 4.1.1

POPULATION ONE N=50

300.
270.
240.
210.
180.
150.
120.
90.
60.
30.
0.

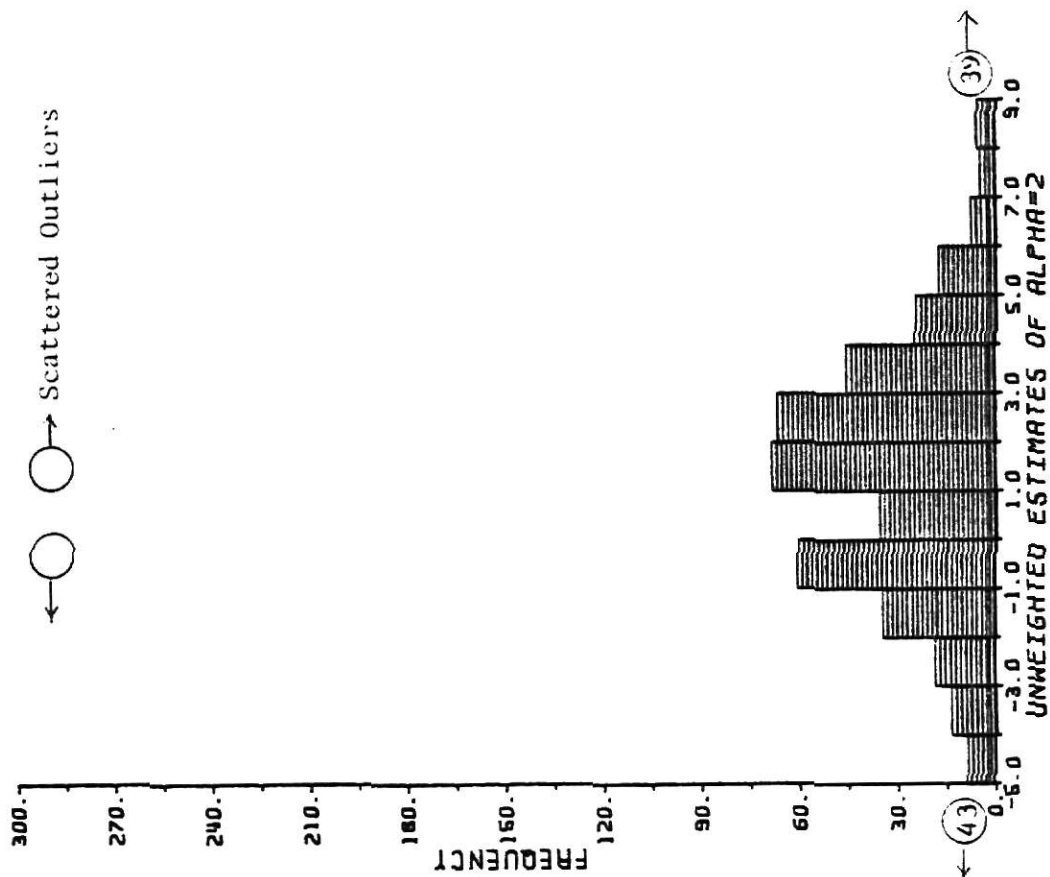
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POPULATION TWO N=50

300.
270.
240.
210.
180.
150.
120.
90.
60.
30.
0.

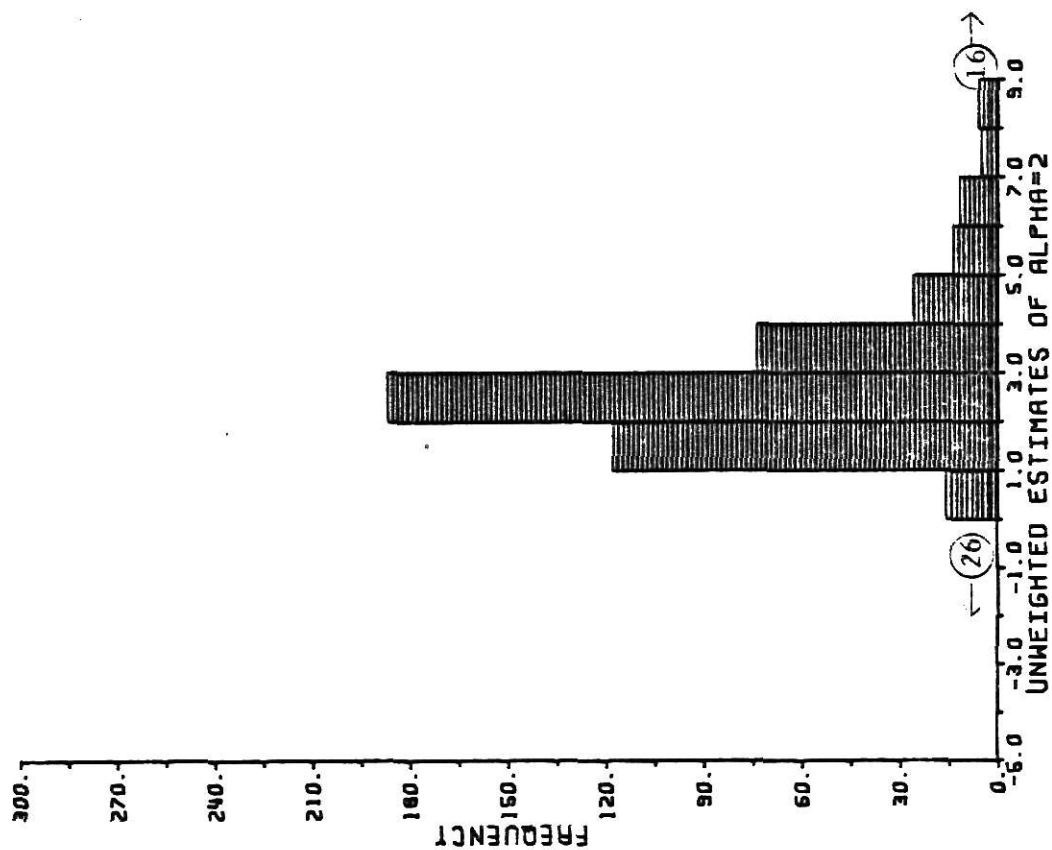
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←○→ Scattered Outliers

Figure 4.1.2

POPULATION ONE N=100



POPULATION TWO N=100

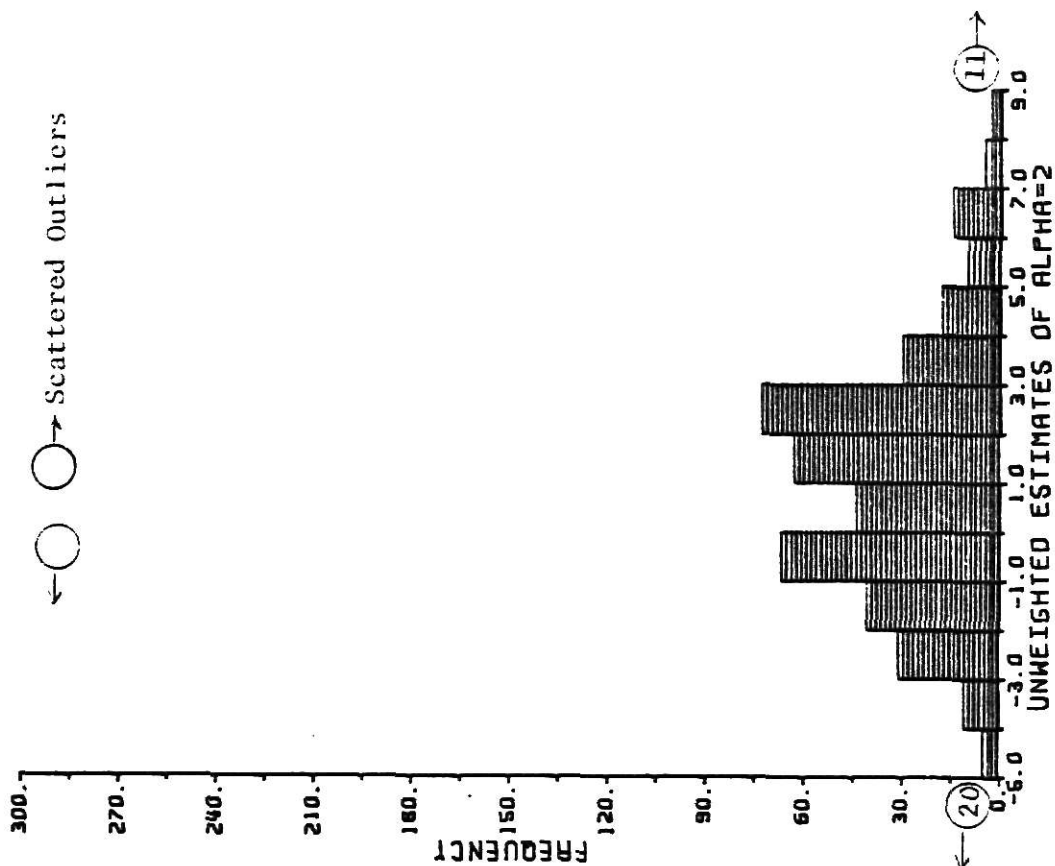


Figure 4.1.3

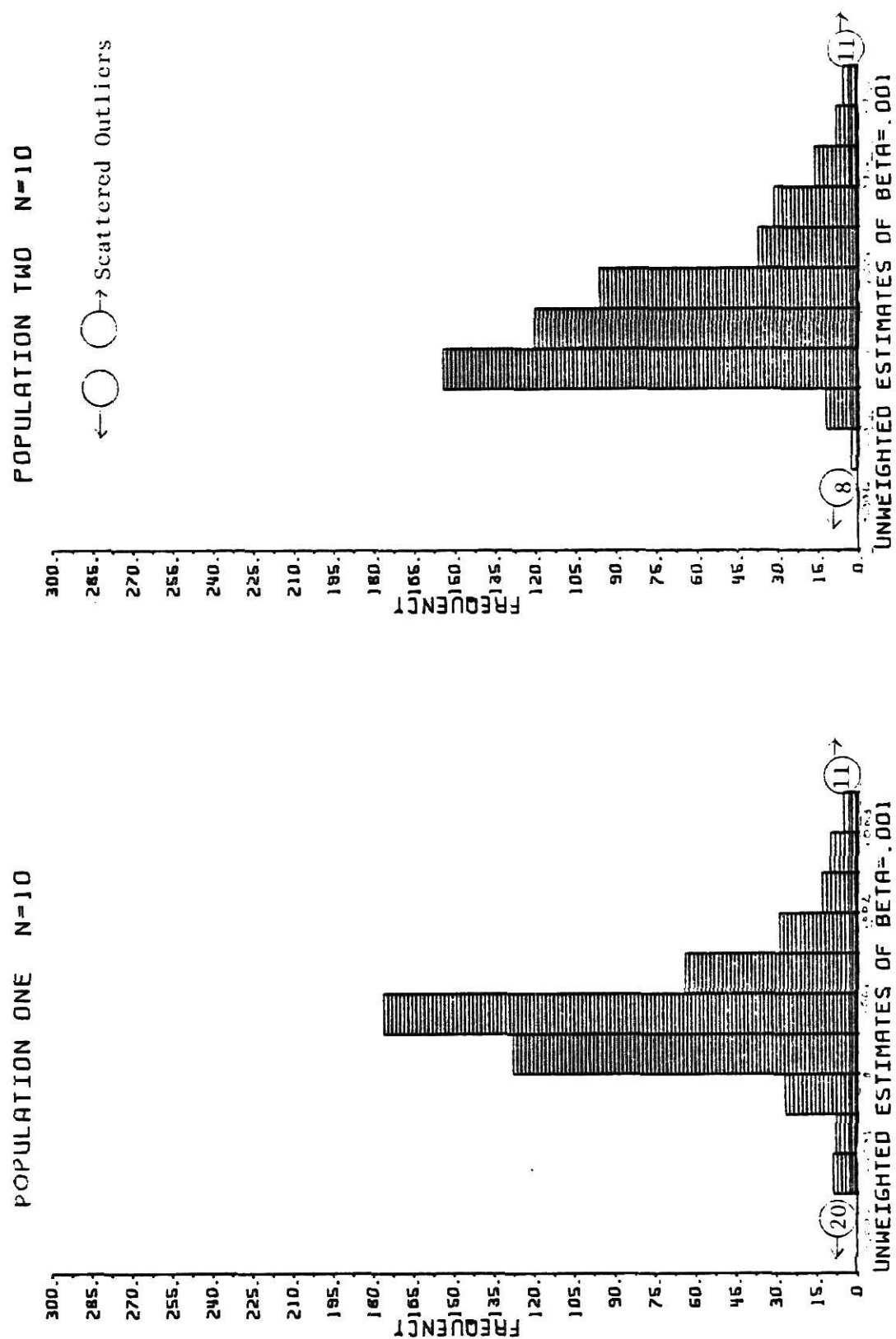


Figure 4.1.4

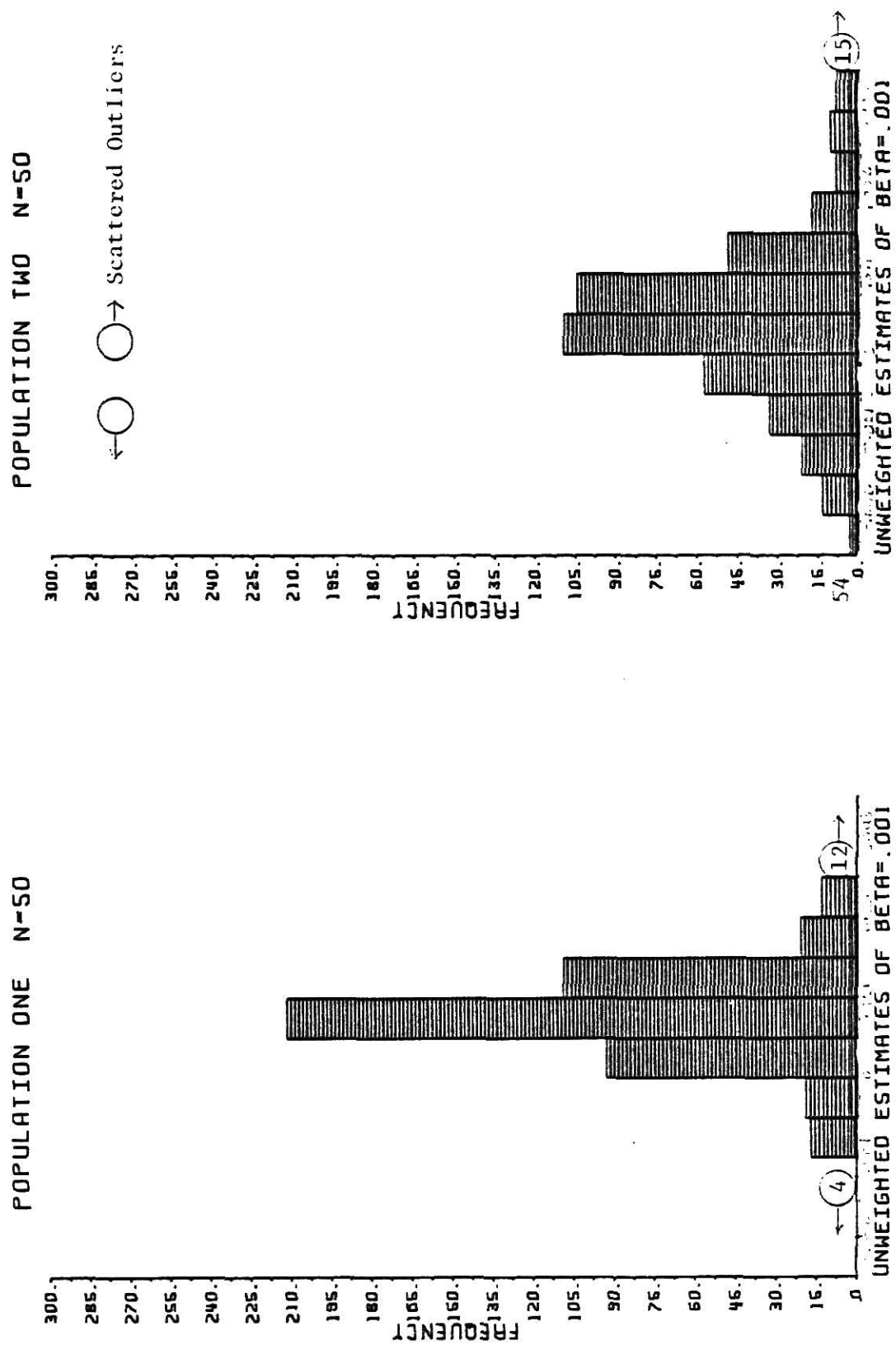


Figure 4.1.5

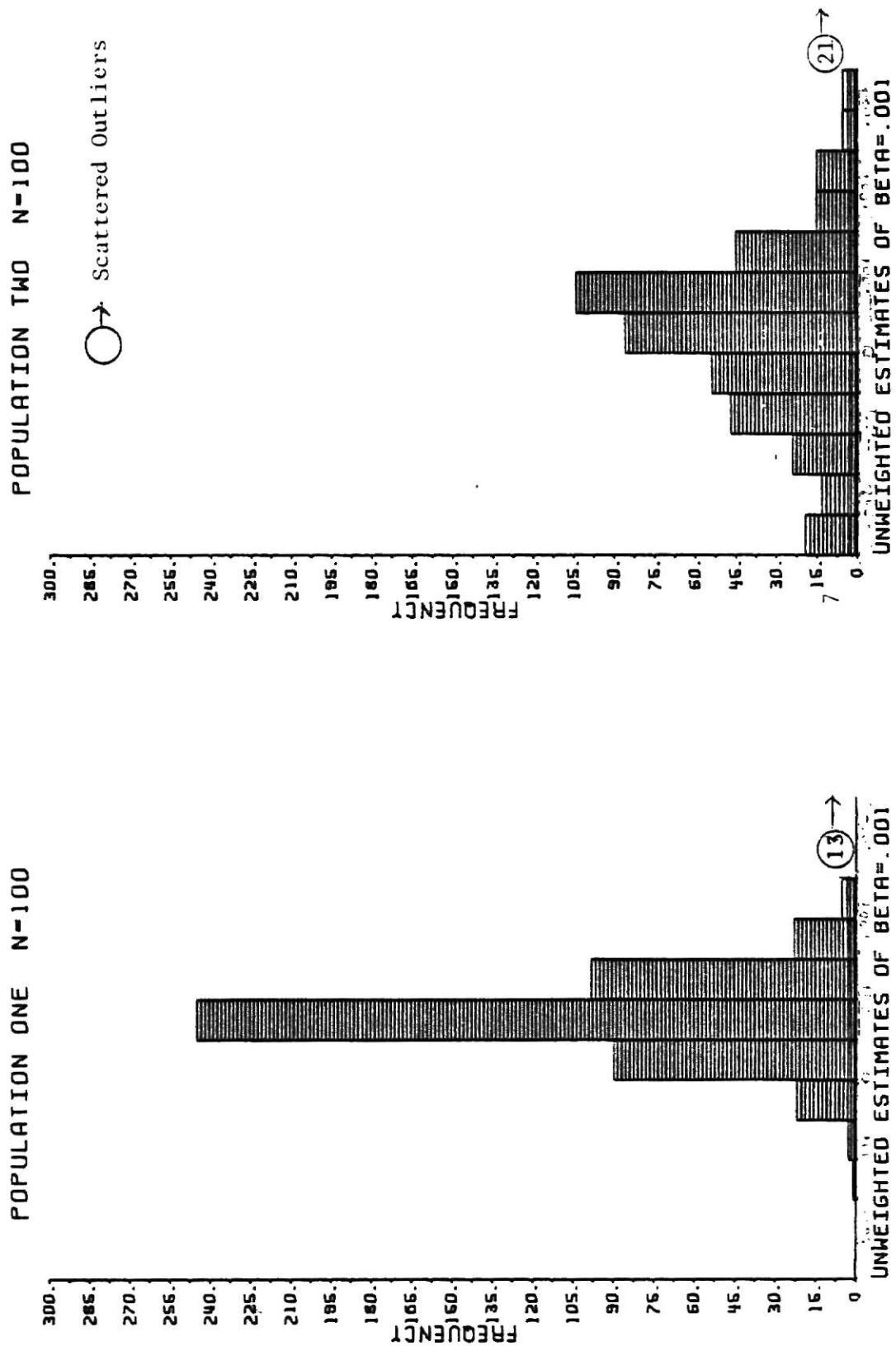
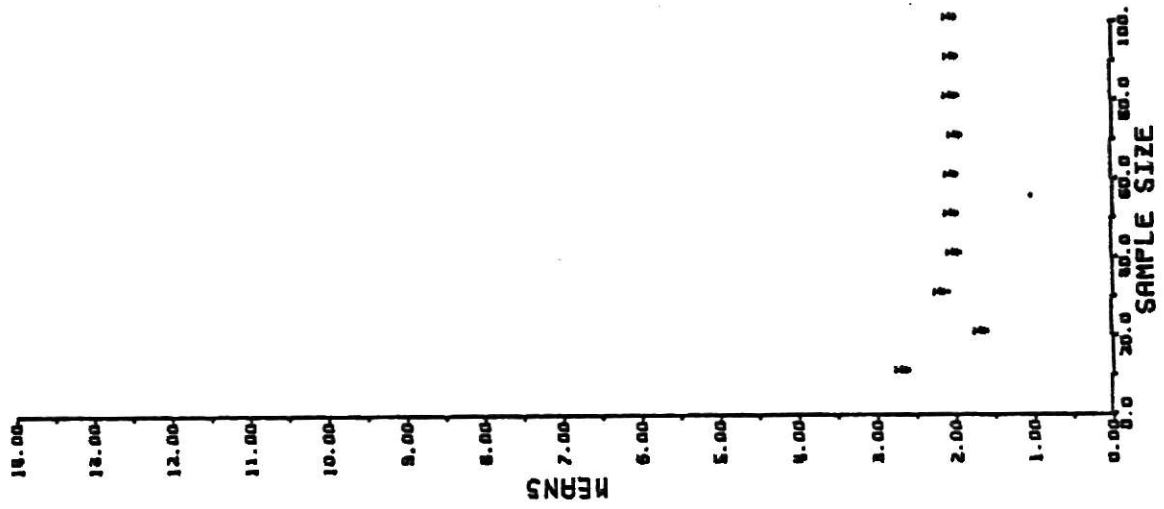
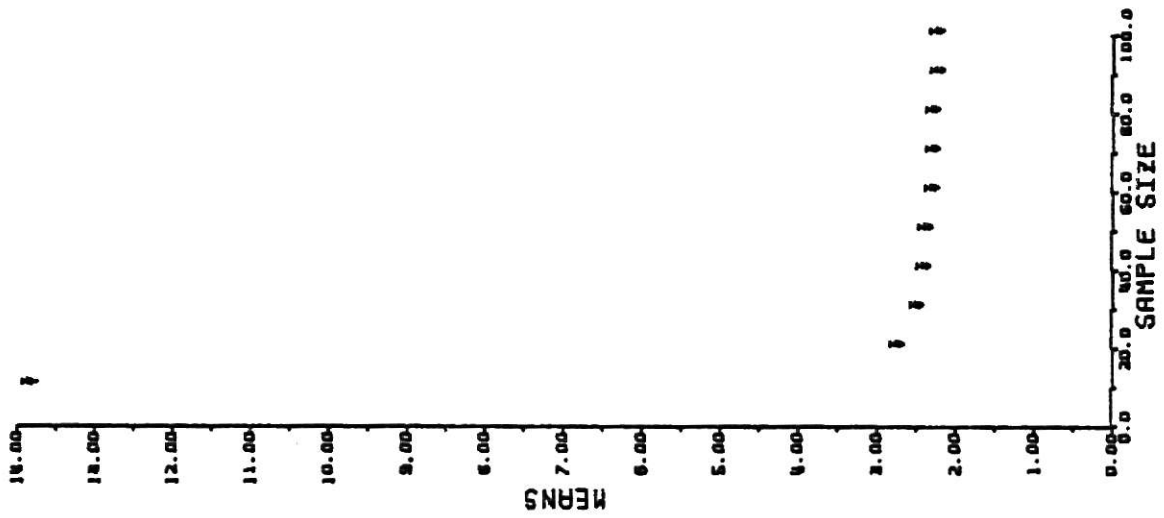


Figure 4.1.6

MLE MEANS ALPHA=2
POPULATION ONE



TIME-WEIGHTED MEANS, ALPHA=2
POPULATION ONE



UNWEIGHTED MEANS, ALPHA=2
POPULATION ONE

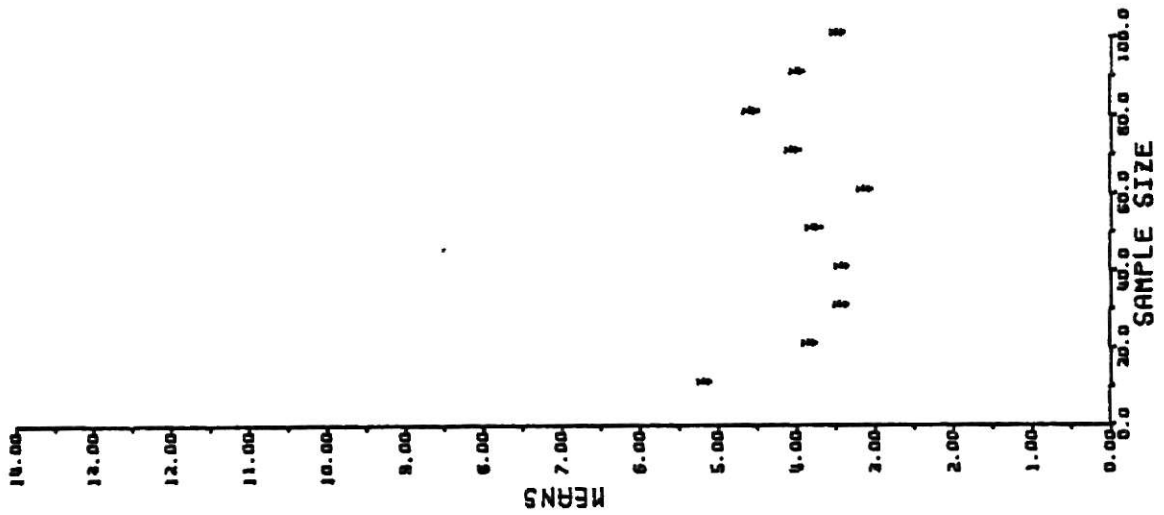


Figure 4.1.7

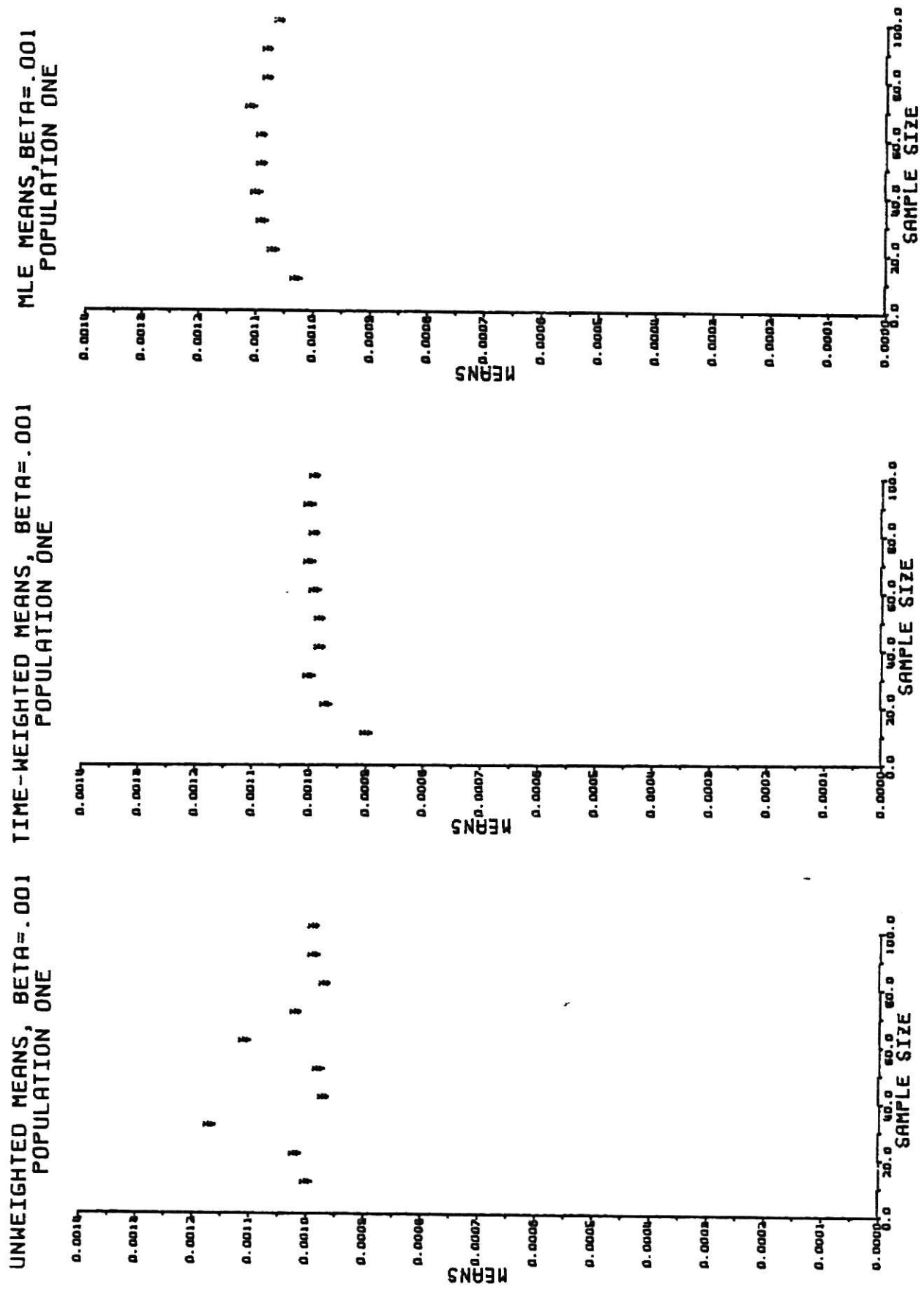


Figure 4.1.8

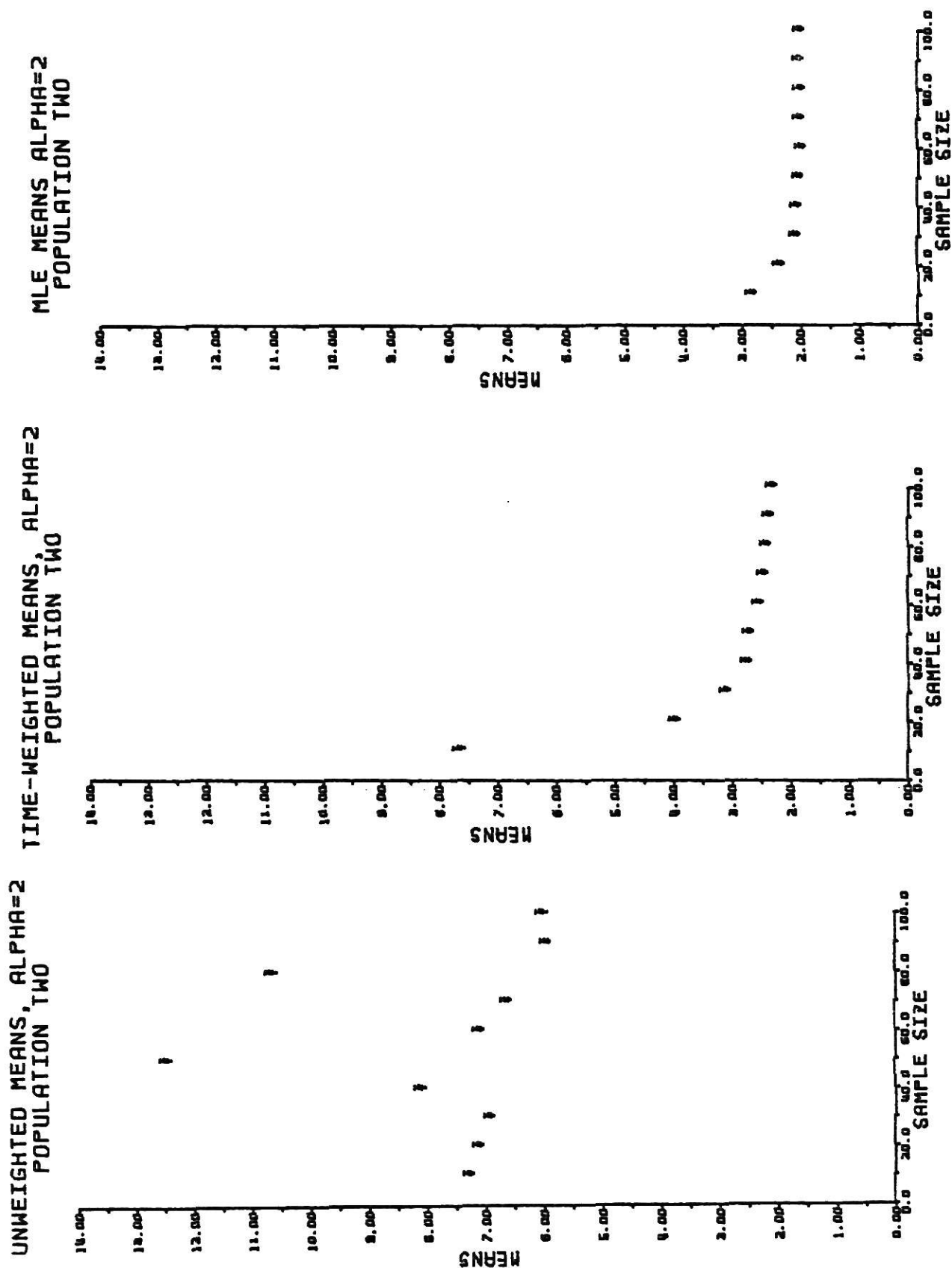


Figure 4.1.9

UNWEIGHTED MEANS, $BETA = .001$ TIME-WEIGHTED MEANS, $BETA = .001$ MLE MEANS, $BETA = .001$
 POPULATION TWO POPULATION TWO POPULATION TWO

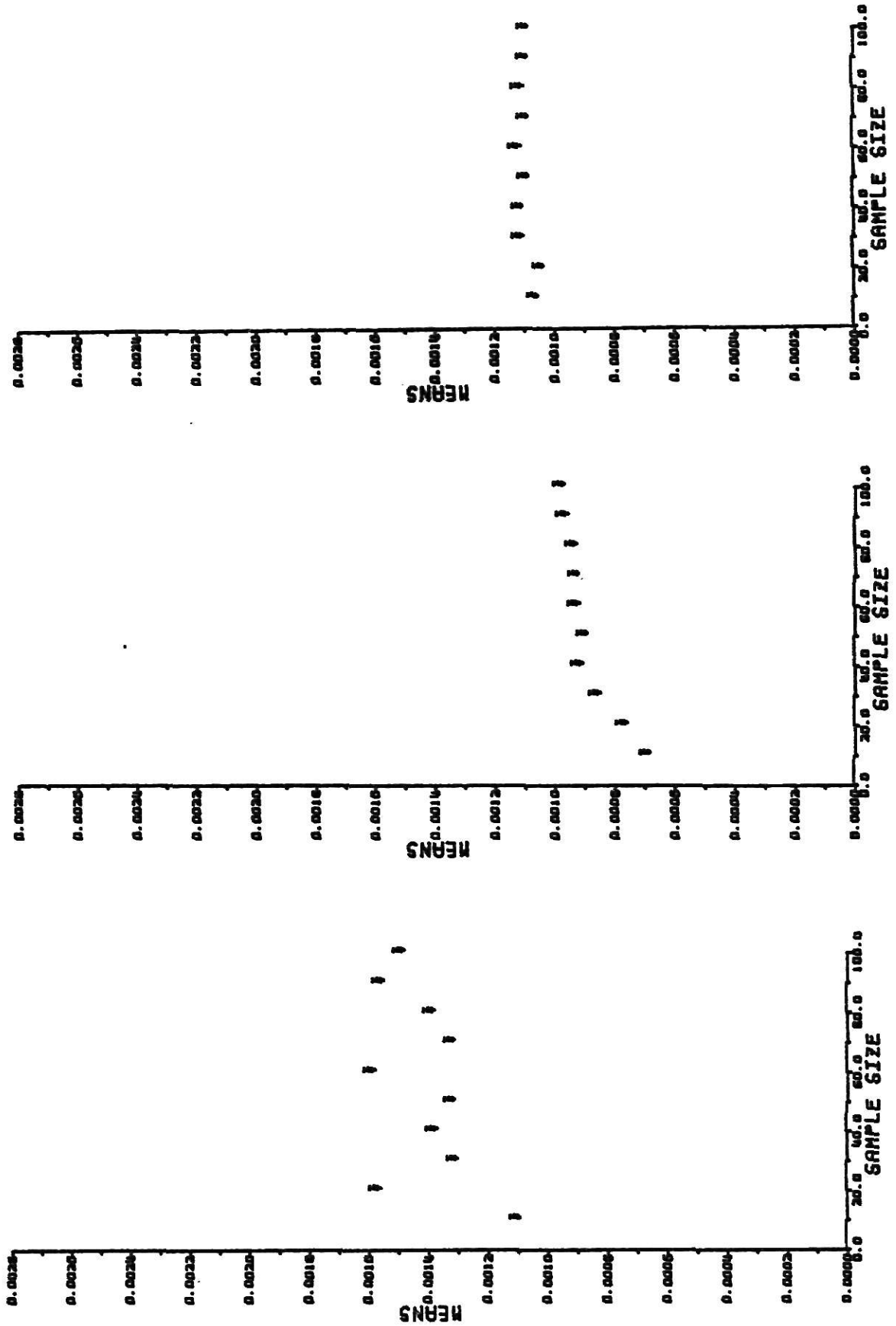


Figure 4.1.10

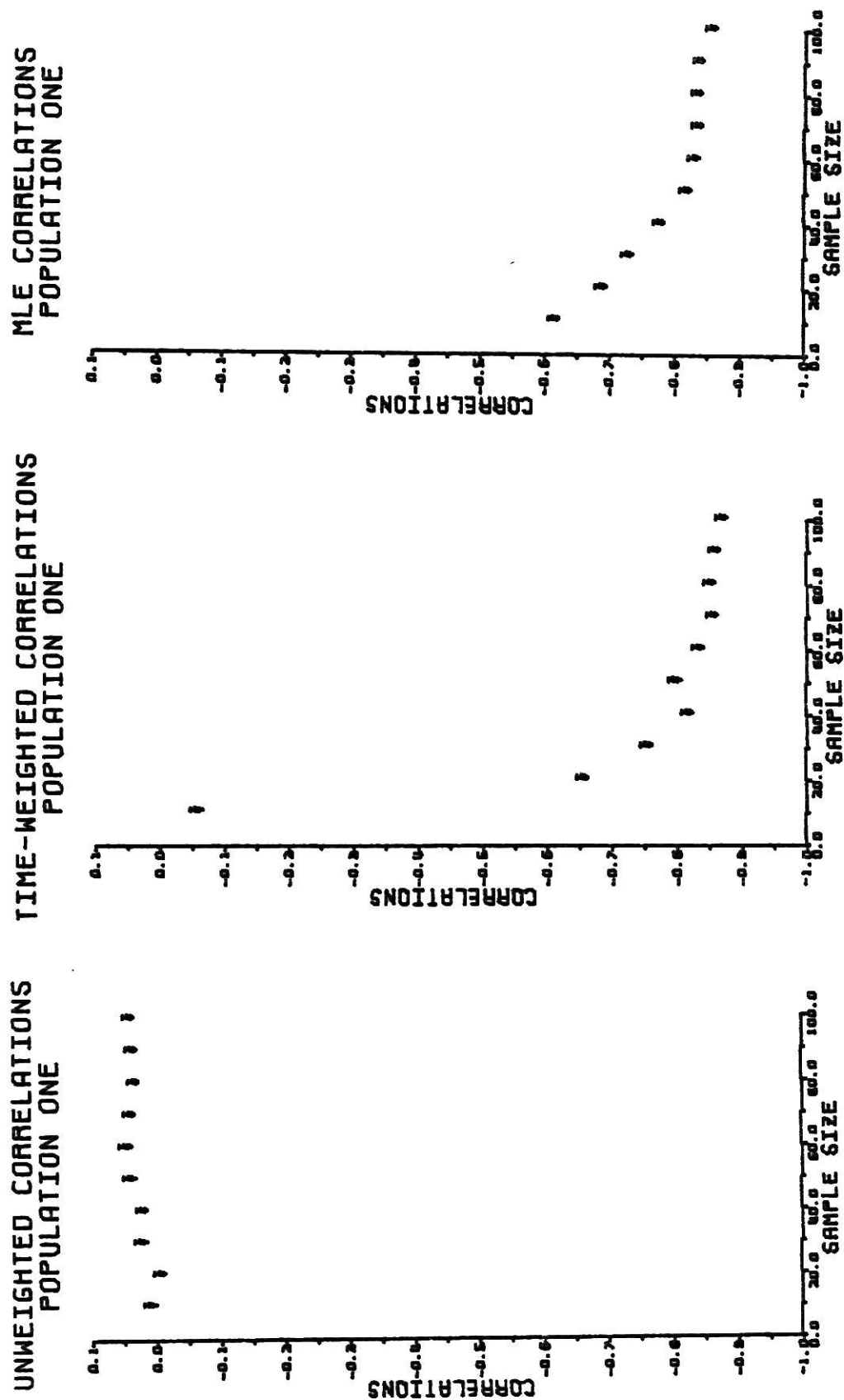


Figure 4.1.11

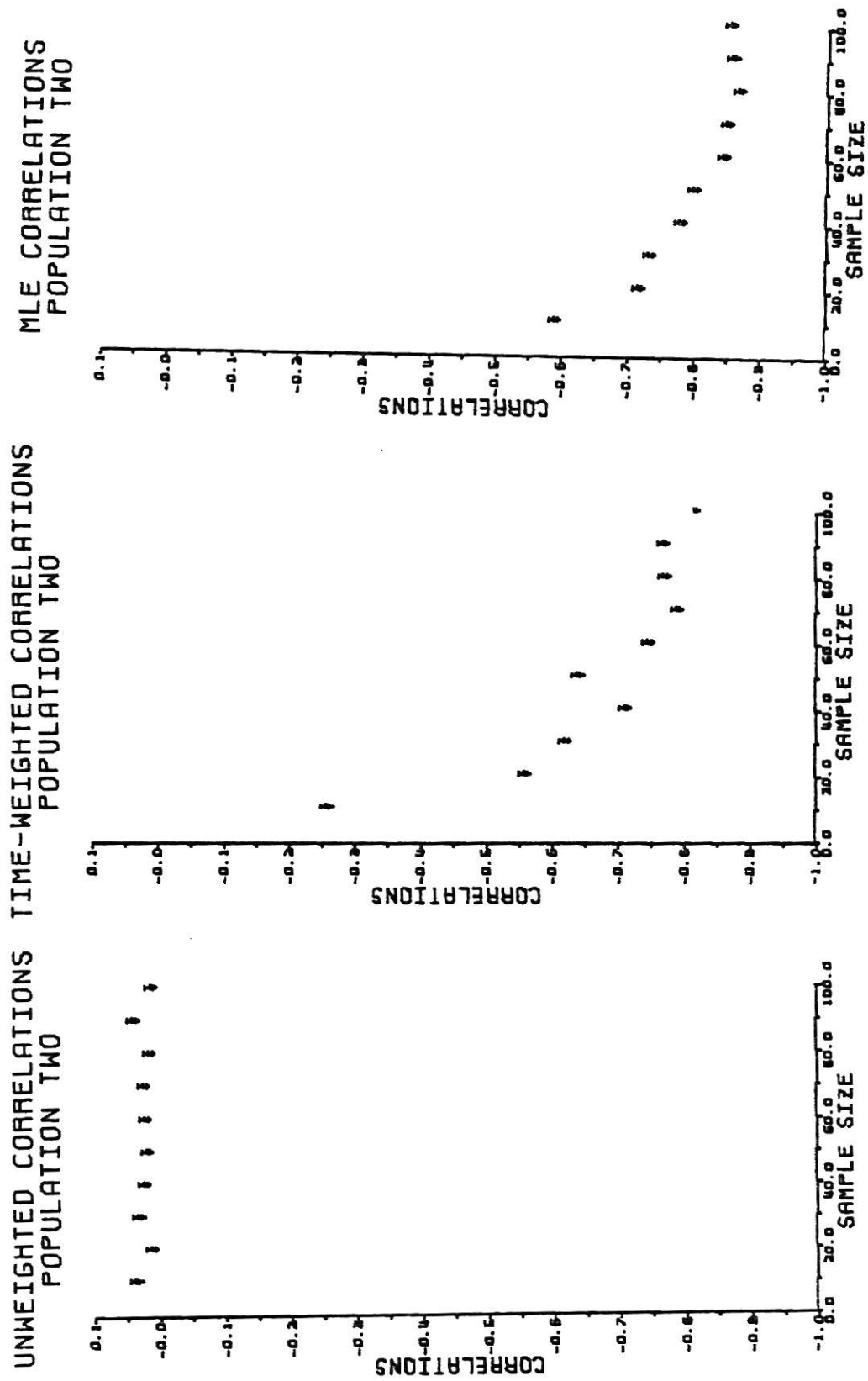


Figure 4.1.12

Table 4.1.1a Typical Samples (Size 10) From Population One

SAMPLE NUMBER	1	TIMES	COUNTS	SAMPLE NUMBER	6	TIMES	COUNTS
		2292	9			850	0
		1660	1			9013	22
		6176	10			5095	21
		6075	10			4302	5
		2128	15			2491	15
		5198	21			4133	12
		9858	27			6898	4
		5809	8			330	2
		2608	6			9542	55
		8347	28			4122	17
SAMPLE NUMBER	2	TIMES	COUNTS	SAMPLE NUMBER	7	TIMES	COUNTS
		6065	25			7645	14
		7064	16			3800	16
		2744	2			9904	13
		3821	12			9633	4
		107	0			3758	16
		6037	28			5898	7
		9235	24			3941	9
		2918	1			8013	29
		8232	2			5339	14
		6368	28			6385	2
SAMPLE NUMBER	3	TIMES	COUNTS	SAMPLE NUMBER	8	TIMES	COUNTS
		872	2			5620	4
		199	0			8428	15
		4143	12			7361	9
		7562	20			8106	3
		6207	14			5606	19
		3032	4			3842	7
		4199	14			2402	1
		1584	9			6472	5
		430	0			1524	5
		9742	22			3722	17
SAMPLE NUMBER	4	TIMES	COUNTS	SAMPLE NUMBER	9	TIMES	COUNTS
		984	0			8264	28
		154	0			120	0
		256	0			9476	24
		4958	11			3917	12
		7966	1			8403	12
		5693	4			9316	26
		9967	22			5690	9
		4351	16			4725	3
		1542	7			3538	10
		9074	28			5124	5
SAMPLE NUMBER	5	TIMES	COUNTS	SAMPLE NUMBER	10	TIMES	COUNTS
		6844	6			8210	11
		7924	4			8343	8
		1396	1			6810	47
		5291	7			2759	2
		3703	7			5758	12
		2897	6			3138	6
		3233	11			3928	5
		730	0			3627	9
		7456	35			6046	4
		6718	5			9777	8

Table 4.1.1a continued

SAMPLE NUMBER 11	TIMES	COUNTS	SAMPLE NUMBER 16	TIMES	CCOUNTS
	4637	10		1020	2
	6640	0		4467	13
	4114	6		1157	2
	4092	0		6754	5
	1034	3		2956	8
	8431	1		6753	5
	5658	6		7927	21
	5503	11		6412	31
	9395	14		680	1
SAMPLE NUMBER 12	8524	25	SAMPLE NUMBER 17	1206	4
	TIMES	CCOUNTS		TIMES	CCOUNTS
	2438	2		3340	12
	1586	3		4538	6
	1508	0		7470	13
	3517	2		844	5
	3000	9		8782	40
	2351	9		6587	2
	9568	24		4475	12
	5218	11		6771	24
SAMPLE NUMBER 13	8510	26	SAMPLE NUMBER 18	2541	3
	5516	1		7336	21
	TIMES	COUNTS		TIMES	CCOUNTS
	4552	1		6754	3
	645	2		3205	4
	756	3		2448	18
	4396	1		1831	4
	1733	2		2111	3
	6089	3		735	2
	7723	8		1656	2
SAMPLE NUMBER 14	2131	17	SAMPLE NUMBER 19	4286	9
	5841	2		5076	12
	5132	8		3130	3
	TIMES	COUNTS		TIMES	CCOUNTS
	3848	11		3147	8
	6075	4		5903	7
	2489	2		6002	5
	2533	13		4582	2
	5066	17		9708	41
	9295	11		5182	7
SAMPLE NUMBER 15	6583	9	SAMPLE NUMBER 20	1332	0
	6787	13		1233	3
	9897	19		1222	0
	7669	13		7109	17
	TIMES	CCOUNTS		TIMES	CCOUNTS
	819	2		5813	18
	9438	11		7358	18
	9368	28		3022	4
	9688	6		7970	28
	8306	38		2643	11
	4425	7		3666	7
	1456	4		7800	26
	463	2		9128	17
	6013	19		5583	26
	4361	4		4557	5

Table 4.1.1a continued

SAMPLE NUMBER	21	TIMES	COUNTS	SAMPLE NUMBER	26	TIMES	COUNTS
		8435	0			7941	6
		2946	7			5934	19
		9489	5			3221	5
		5417	2			9506	2
		1909	0			3890	14
		1886	2			6155	20
		625	2			9364	6
		6293	4			1683	0
		7500	22			9628	17
		5626	18			9908	17
SAMPLE NUMBER	22	TIMES	COUNTS	SAMPLE NUMBER	27	TIMES	COUNTS
		9487	14			520	0
		1089	2			8202	27
		5952	37			4604	2
		9788	15			2670	5
		8019	33			4385	4
		4556	7			3345	9
		6166	16			6383	19
		4866	7			5853	5
		1813	3			8075	20
		4133	6			374	0
SAMPLE NUMBER	23	TIMES	COUNTS	SAMPLE NUMBER	28	TIMES	COUNTS
		7367	22			4534	7
		218	0			7048	18
		1328	0			3032	9
		5046	15			1168	6
		5888	17			5654	5
		2294	5			8825	9
		4236	0			8804	13
		9054	44			8574	10
		9212	29			6596	3
		9454	12			6186	12
SAMPLE NUMBER	24	TIMES	COUNTS	SAMPLE NUMBER	29	TIMES	COUNTS
		3406	9			2534	1
		846	3			2894	9
		5907	3			145	0
		6250	16			5317	1
		8688	0			8470	6
		3541	17			2606	0
		827	4			7009	1
		6680	11			3221	9
		399	1			5376	7
		9622	12			8779	8
SAMPLE NUMBER	25	TIMES	COUNTS	SAMPLE NUMBER	30	TIMES	COUNTS
		404	1			6611	23
		474	0			2754	4
		236	0			7210	9
		1316	4			8965	18
		2438	2			416	0
		6294	3			529	3
		1320	0			5027	1
		8812	29			3328	19
		8508	29			1164	1
		1847	2			6338	4

Table 4.1.1a continued

SAMPLE NUMBER	31	TIMES	CCUNTS	SAMPLE NUMBER	36	TIMES	CCUNTS
		5894	4			9261	11
		2734	1			1282	3
		8259	4			749	2
		3813	10			2095	2
		9586	21			3188	2
		1869	3			8415	6
		1766	3			2871	4
		4503	8			7421	6
		5983	7			99	0
		5860	11			8438	5
SAMPLE NUMBER	32	TIMES	CCUNTS	SAMPLE NUMBER	37	TIMES	CCUNTS
		2433	2			2348	14
		999	2			7051	12
		8355	0			1486	2
		8379	53			3622	7
		4492	5			2599	3
		6854	25			3919	3
		5948	4			9244	13
		185	0			5981	11
		7327	10			5786	14
		7818	21			8296	2
SAMPLE NUMBER	33	TIMES	CCUNTS	SAMPLE NUMBER	38	TIMES	CCUNTS
		4461	12			6509	6
		3135	8			6219	6
		4171	14			5690	2
		7741	21			6441	9
		9461	14			3417	6
		4955	1			1488	2
		4516	5			8188	21
		7540	4			9480	28
		4771	14			1732	9
		8818	10			8372	24
SAMPLE NUMBER	34	TIMES	CCUNTS	SAMPLE NUMBER	39	TIMES	CCUNTS
		9653	8			7089	7
		1679	2			3636	7
		8352	36			1526	2
		2039	12			7421	9
		5300	7			4373	9
		5120	7			1073	1
		6845	3			1755	1
		167	0			2419	1
		8787	14			6317	11
		3598	7			468	0
SAMPLE NUMBER	35	TIMES	CCUNTS	SAMPLE NUMBER	40	TIMES	CCUNTS
		3088	6			457	0
		2432	14			2975	8
		5356	25			1823	0
		42	0			9156	16
		7756	29			6745	13
		9051	12			1045	5
		3381	13			3403	20
		6415	6			2307	1
		4973	13			9352	13
		2015	1			7467	16

Table 4.1.1a continued

SAMPLE NUMBER	41	TIMES	COUNTS	SAMPLE NUMBER	46	TIMES	COUNTS
		1868	6			17	0
		4302	4			2548	4
		3933	4			6822	23
		3163	14			5570	4
		560	0			7419	12
		7449	3			498	1
		1052	1			6132	8
		843	0			8255	4
		1012	0			386	2
		5705	3			3378	16
SAMPLE NUMBER	42	TIMES	COUNTS	SAMPLE NUMBER	47	TIMES	COUNTS
		2057	4			9593	21
		5157	6			255	0
		7767	7			9662	26
		718	2			7034	11
		527	0			8905	9
		271	0			4452	4
		6454	9			8210	20
		5536	11			5255	11
		1287	6			5439	2
		8205	48			4154	6
SAMPLE NUMBER	43	TIMES	COUNTS	SAMPLE NUMBER	48	TIMES	COUNTS
		3678	4			310	2
		3903	10			2743	14
		8716	36			2435	18
		1054	1			5952	9
		1026	0			4158	0
		7188	15			1348	3
		3865	4			918	2
		4667	3			2782	7
		1875	0			9727	3
		9770	13			5103	1
SAMPLE NUMBER	44	TIMES	COUNTS	SAMPLE NUMBER	49	TIMES	COUNTS
		6123	13			8530	2
		9829	28			6058	10
		3794	11			7644	14
		1908	4			5422	2
		6357	15			6017	3
		7614	7			35	1
		5480	2			228	1
		8216	10			1692	6
		9711	25			4212	3
		2129	3			1487	3
SAMPLE NUMBER	45	TIMES	COUNTS	SAMPLE NUMBER	50	TIMES	COUNTS
		1712	1			7394	26
		8551	7			2713	8
		5145	18			6211	12
		6717	57			676	0
		3044	2			2336	2
		3122	8			8779	27
		4164	22			6419	2
		2073	7			3479	8
		347	2			4302	14
		7628	12			6578	6

Table 4.1.1b Typical Samples (Size 10) from Population Two

SAMPLE NUMBER	1	TIMES	CCUNTS	SAMPLE NUMBER	6	TIMES	CCUNTS
		22925	189			735	1
		706	4			16563	34
		3537	7			3147	7
		2744	1			5903	6
		38218	78			600	0
		694	2			3269	4
		9017	24			5453	39
		87	0			35	0
		143	0			652	2
		41437	11			504	0
SAMPLE NUMBER	2	TIMES	CCUNTS	SAMPLE NUMBER	7	TIMES	CCUNTS
		75621	188			182	2
		907	5			178	0
		98526	507			7109	16
		265	0			5813	17
		42739	98			7358	17
		1201	2			302	0
		249	0			41764	67
		52183	258			9896	34
		22557	10			2607	6
		4114	5			482	2
SAMPLE NUMBER	3	TIMES	CCUNTS	SAMPLE NUMBER	8	TIMES	CCUNTS
		409	0			6403	9
		80364	253			5588	4
		15753	10			61	0
		38484	15			3432	5
		216	0			835	0
		38495	1			607	0
		9828	35			1512	0
		4208	5			112	0
		65831	62			81089	21
		8192	15			2730	5
SAMPLE NUMBER	4	TIMES	CCUNTS	SAMPLE NUMBER	9	TIMES	CCUNTS
		9368	27			2244	6
		968	4			87811	130
		7873	38			455	1
		44252	40			64930	518
		4361	3			168	1
		1020	1			71790	14
		44678	12			99089	49
		1157	4			460	0
		98281	81			91	0
		304	2			1571	4
SAMPLE NUMBER	5	TIMES	CCUNTS	SAMPLE NUMBER	10	TIMES	CCUNTS
		622	1			69389	72
		660	0			8304	27
		722	2			4262	5
		804	0			68385	95
		766	3			582	2
		74706	115			682	1
		7779	21			260	0
		675	1			928	0
		1155	1			2722	7
		9964	33			5376	6

SAMPLE NUMBER 11	TIMES	CCUNTS	SAMPLE NUMBER 16	TIMES	CCUNTS
	877	0		329	0
	2910	21		97126	248
	9593	23		85305	229
	8965	17		43918	47
	41	0		74871	469
	6788	19		2106	3
	89668	212		90128	225
	77412	180		858	1
	916	0		660	1
SAMPLE NUMBER 12	732	2	SAMPLE NUMBER 17	360	4
	TIMES	CCUNTS		TIMES	CCUNTS
	19649	73		581	5
	39730	94		31130	37
	2452	6		492	0
	1282	2		973	4
	7495	4		96950	317
	5859	6		26799	64
	320	0		6969	9
	563	0		32892	46
SAMPLE NUMBER 13	13329	10	SAMPLE NUMBER 18	433	1
	99	0		659	2
	TIMES	CCUNTS		TIMES	CCUNTS
	650	1		732	1
	877	2		14230	23
	10835	45		207	0
	39194	89		500	1
	34177	65		760	1
	17322	35		988	0
	7089	6		3008	2
SAMPLE NUMBER 14	3636	6	SAMPLE NUMBER 19	9445	7
	15266	13		46047	20
	43731	39		7079	10
	TIMES	CCUNTS		TIMES	CCUNTS
	568	2		203	0
	35632	122		19436	46
	98633	360		58514	258
	40902	68		46788	71
	4745	1		65271	143
	435	1		598	2
SAMPLE NUMBER 15	820	3	SAMPLE NUMBER 20	8940	15
	949	0		67964	63
	19815	79		8373	26
	3122	7		26536	81
	TIMES	CCUNTS		TIMES	CCUNTS
	4164	21		84	2
	2073	6		9000	11
	3475	14		937	2
	335	0		2375	14
	713	1		5071	3
	8096	27		719	0
	251	0		9212	7
	5446	12		27071	55
	498	1		775	0
	7511	10		70442	57

Table 4.1.1b continued

SAMPLE NUMBER	21	TIMES	CCUNTS	SAMPLE NUMBER	26	TIMES	CCUNTS
		3859	3			928	5
		588	0			2524	29
		583	1			39771	99
		586	4			7626	7
		734	2			8528	12
		5302	4			3690	13
		20710	38			5477	16
		72045	70			494	0
		2310	6			9414	17
		1369	2			9022	17
SAMPLE NUMBER	22	TIMES	CCUNTS	SAMPLE NUMBER	27	TIMES	CCUNTS
		797	0			295	0
		32	0			962	2
		385	0			612	1
		822	0			617	1
		47050	56			102	0
		2445	9			1931	1
		6206	18			397	1
		1535	3			962	1
		7762	26			78207	92
		53232	61			17590	13
SAMPLE NUMBER	23	TIMES	CCUNTS	SAMPLE NUMBER	28	TIMES	CCUNTS
		527	4			9155	11
		4031	28			1030	1
		123	0			8761	16
		7517	15			9166	13
		957	1			36867	64
		975	1			16338	30
		671	1			50431	108
		128	1			1063	2
		72192	133			8393	16
		3941	6			54308	70
SAMPLE NUMBER	24	TIMES	CCUNTS	SAMPLE NUMBER	29	TIMES	CCUNTS
		6945	6			5561	5
		50	0			807	4
		679	1			2521	1
		4534	8			63753	98
		269	1			1921	5
		40354	39			9136	10
		27657	7			4232	3
		80538	318			8746	5
		2084	3			272	0
		778	2			763	6
SAMPLE NUMBER	25	TIMES	CCUNTS	SAMPLE NUMBER	30	TIMES	CCUNTS
		85500	180			625	2
		328	0			21405	14
		358	0			8080	2
		768	2			992	1
		173	0			63368	39
		91008	114			7364	17
		8069	28			842	0
		5253	16			71213	39
		772	2			86918	183
		57851	147			4140	8

SAMPLE NUMBER 31	TIMES	COUNTS	SAMPLE NUMBER 36	TIMES	COUNTS
	594	2		623	0
	494	0		1289	11
	2055	8		57655	51
	3987	16		390	0
	656	1		9180	22
	27220	24		55989	89
	521	0		9135	8
	7401	43		61041	49
	62746	394		6240	4
	28026	29		209	0
SAMPLE NUMBER 32	TIMES	COUNTS	SAMPLE NUMBER 37	TIMES	COUNTS
	3965	1		5834	6
	8832	10		8782	42
	5798	8		811	1
	129	0		104	0
	2787	2		31134	27
	781	2		685	0
	93	0		42335	159
	158	0		751	3
	14932	12		287	0
	4481	9		70862	31
SAMPLE NUMBER 33	TIMES	COUNTS	SAMPLE NUMBER 38	TIMES	COUNTS
	572	5		9162	40
	6878	12		19849	30
	664	3		6166	5
	7234	13		417	0
	19396	45		8387	6
	306	1		835	6
	1011	2		75539	53
	36280	30		900	0
	86942	93		4772	7
	77222	164		1664	4
SAMPLE NUMBER 34	TIMES	COUNTS	SAMPLE NUMBER 39	TIMES	COUNTS
	3889	2		36387	82
	3178	3		679	1
	55118	273		12638	25
	41888	85		192	0
	233	0		144	1
	3729	2		6215	4
	776	0		7705	48
	56329	158		8422	19
	3677	5		69	2
	9381	11		990	3
SAMPLE NUMBER 35	TIMES	COUNTS	SAMPLE NUMBER 40	TIMES	COUNTS
	54910	95		27999	130
	4661	4		1465	0
	795	0		6936	14
	429	1		713	2
	87465	111		653	1
	146	0		7647	25
	875	1		6949	5
	526	0		16137	8
	27872	10		55851	72
	9591	11		4188	2

Table 4.1.1b continued

SAMPLE NUMBER 41	TIMES	CCUNTS	SAMPLE NUMBER 46	TIMES	CCUNTS
	8796	22		723	2
	185	0		80600	272
	297	1		67922	3
	383	0		89728	268
	56800	107		2681	3
	227	1		9568	18
	2036	7		315	0
	7362	8		62341	157
	65539	61		556	2
	5909	17		8175	25
SAMPLE NUMBER 42	TIMES	CCUNTS	SAMPLE NUMBER 47	TIMES	CCUNTS
	40495	62		915	0
	250	0		59987	39
	98555	45		601	1
	6523	0		784	0
	32569	53		5214	10
	884	3		17	0
	299	0		2113	5
	47301	87		2782	1
	272	1		8675	26
	6089	8		435	0
SAMPLE NUMBER 43	TIMES	CCUNTS	SAMPLE NUMBER 48	TIMES	CCUNTS
	5015	7		90551	147
	49652	16		807	1
	16514	44		356	0
	105	0		3993	1
	1379	0		1695	1
	933	1		9206	7
	64729	119		903	0
	21604	44		145	0
	25188	102		311	0
	3936	12		749	2
SAMPLE NUMBER 44	TIMES	CCUNTS	SAMPLE NUMBER 49	TIMES	CCUNTS
	7593	7		73689	228
	3591	1		83479	399
	135	0		96132	12
	1878	0		96452	249
	73297	178		5229	5
	83070	262		27572	61
	9151	8		9746	37
	908	1		33164	14
	517	3		538	4
	288	3		895	3
SAMPLE NUMBER 45	TIMES	CCUNTS	SAMPLE NUMBER 50	TIMES	CCUNTS
	292	1		663	1
	366	0		6458	13
	416	0		3893	6
	34359	83		2642	3
	9551	25		500	0
	670	3		676	4
	29131	12		95591	61
	94264	136		7574	18
	8	0		858	4
	42876	142		57527	104

Table 4.1.2 Summary Statistics for $\hat{\alpha}$ and $\hat{\beta}$ for all Cases.

POPEN=1 N=10					
VARIABLE	N	MEAN	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
AUN ($\hat{\alpha}_u$)	500	2.86831495	21.14356147	-377.71375438	120.47584447
AMLE ($\hat{\alpha}_{MLE}$)	385	2.57044330	1.75020573	0.54103562	15.30937720
ATW ($\hat{\alpha}_T$)	500	13.73877788	244.77927948	-471.12075688	5437.72022431
AC ($\hat{\alpha}_c$)	500	1.78880671	0.99360734	0.25847269	3.99774759
BUN ($\hat{\beta}_u$)	500	0.00066747	0.00157634	-0.01023562	0.01339748
BMLE ($\hat{\beta}_{MLE}$)	385	0.00102044	0.00056952	0.00012054	0.00369205
BTW ($\hat{\beta}_T$)	500	0.00089145	0.00064762	-0.00009997	0.00584707
BC ($\hat{\beta}_c$)	500	0.00143134	0.00127644	0.00022942	0.01691968
----- POPEN=1 N=20 -----					
AUN ($\hat{\alpha}_u$)	500	2.68974141	7.23345482	-64.55432561	72.50353339
AMLE ($\hat{\alpha}_{MLE}$)	383	2.19237651	1.09218448	0.81499530	11.22754453
ATW ($\hat{\alpha}_T$)	500	2.62805670	1.50394850	0.62024749	13.28019968
AC ($\hat{\alpha}_c$)	500	1.57296626	0.60614224	0.17813306	4.93644141
BUN ($\hat{\beta}_u$)	500	0.00079580	0.00135681	-0.00443949	0.01872417
BMLE ($\hat{\beta}_{MLE}$)	383	0.00106169	0.00040853	0.00015294	0.00242917
BTW ($\hat{\beta}_T$)	500	0.00064553	0.00054552	0.00013448	0.00413562
BC ($\hat{\beta}_c$)	500	0.00152732	0.00130292	0.00039950	0.02135745
----- POPEN=1 N=30 -----					
AUN ($\hat{\alpha}_u$)	500	1.62712646	11.88926061	-205.10704120	60.37376985
AMLE ($\hat{\alpha}_{MLE}$)	362	2.09429297	0.84162310	0.84120049	9.67324313
ATW ($\hat{\alpha}_T$)	500	2.37829785	1.13079438	0.69615111	11.56535040
AC ($\hat{\alpha}_c$)	500	1.46199523	0.51216395	0.09591127	3.32870813
BUN ($\hat{\beta}_u$)	500	0.00097369	0.00225004	-0.00237670	0.04460259
BMLE ($\hat{\beta}_{MLE}$)	362	0.00107527	0.00035879	0.00018054	0.00256728
BTW ($\hat{\beta}_T$)	500	0.00098850	0.00042664	0.00014840	0.00305167
BC ($\hat{\beta}_c$)	500	0.00170166	0.00236389	0.00051600	0.04337636
----- POPEN=1 N=40 -----					
AUN ($\hat{\alpha}_u$)	500	2.25434716	7.69585810	-117.20745603	42.48550417
AMLE ($\hat{\alpha}_{MLE}$)	342	1.92303906	0.46182491	1.15701131	4.06159035
ATW ($\hat{\alpha}_T$)	500	2.30470062	0.84313145	0.81801577	7.68972455
AC ($\hat{\alpha}_c$)	500	1.47394636	0.45493956	0.15553903	3.19460875
BUN ($\hat{\beta}_u$)	500	0.00083433	0.00111106	-0.00157724	0.01996949
BMLE ($\hat{\beta}_{MLE}$)	342	0.00109434	0.00025659	0.00053006	0.00192346
BTW ($\hat{\beta}_T$)	500	0.00096886	0.00033441	0.00025443	0.00215893
BC ($\hat{\beta}_c$)	500	0.00152230	0.00111330	0.00058112	0.02192685
----- POPEN=1 N=50 -----					
AUN ($\hat{\alpha}_u$)	500	-0.31707720	64.98230548	-1437.52300977	110.60665112
AMLE ($\hat{\alpha}_{MLE}$)	299	1.94613576	0.42687501	1.07292574	3.70269778
ATW ($\hat{\alpha}_T$)	500	2.27233467	0.72082036	0.52423270	6.30578566
AC ($\hat{\alpha}_c$)	500	1.44130233	0.41347668	0.15259209	2.96667660
BUN ($\hat{\beta}_u$)	500	0.00084636	0.00108832	-0.00214688	0.01730302
BMLE ($\hat{\beta}_{MLE}$)	299	0.00108134	0.00024793	0.00055075	0.00196805
BTW ($\hat{\beta}_T$)	500	0.00096836	0.00035261	0.00030713	0.00344424
BC ($\hat{\beta}_c$)	500	0.00155941	0.00105695	0.00065955	0.01363581

Table 4.1.2 (cont).

PCPN=1 N=60					
VARIABLE	N	MEAN	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
ALN ($\hat{\alpha}_U$)	500	1.29054370	10.53146769	-130.35017431	73.91826896
AMLE ($\hat{\alpha}_{MLE}$)	290	1.95398125	0.45100984	1.15330654	4.39083237
ATW ($\hat{\alpha}_T$)	500	2.18766434	0.60014622	0.88756181	5.04663996
AC ($\hat{\alpha}_C$)	500	1.39110927	0.36815960	0.11603380	2.62909953
BUN ($\hat{\beta}_U$)	500	0.00095278	0.00134127	-0.00220243	0.00232129
BMLE ($\hat{\beta}_{MLE}$)	280	0.00107526	0.00025195	0.00043821	0.00191717
BTW ($\hat{\beta}_T$)	500	0.00097824	0.00030776	0.00030455	0.00234714
BC ($\hat{\beta}_C$)	500	0.00168889	0.00135992	0.00071403	0.00244479
----- PCPN=1 N=70 -----					
ALN ($\hat{\alpha}_U$)	500	0.62357246	32.44718825	-469.65394587	173.77352272
AMLE ($\hat{\alpha}_{MLE}$)	237	1.90267874	0.37934961	1.23822030	3.54757691
ATW ($\hat{\alpha}_T$)	500	2.18490014	0.61039014	0.77703827	5.10550269
AC ($\hat{\alpha}_C$)	500	1.41188813	0.35187696	0.13773689	2.73721781
BUN ($\hat{\beta}_U$)	500	0.00091965	0.00141330	-0.00117306	0.00200257
BMLE ($\hat{\beta}_{MLE}$)	237	0.00109746	0.00021661	0.00049530	0.00171493
BTW ($\hat{\beta}_T$)	500	0.00098666	0.00029064	0.00034661	0.00237990
BC ($\hat{\beta}_C$)	500	0.00162542	0.00150135	0.00075368	0.00275115
----- PCPN=1 N=80 -----					
ALN ($\hat{\alpha}_U$)	500	-2.93540747	151.21815558	-3346.54007746	414.82029657
AMLE ($\hat{\alpha}_{MLE}$)	220	1.95822467	0.37378138	1.28029094	3.44056935
ATW ($\hat{\alpha}_T$)	500	2.17751326	0.54637655	0.87893410	4.24736719
AC ($\hat{\alpha}_C$)	500	1.38862416	0.32711119	0.12715540	2.42748749
BUN ($\hat{\beta}_U$)	500	0.00090720	0.00123420	-0.00068870	0.00202795
BMLE ($\hat{\beta}_{MLE}$)	220	0.00106950	0.00020636	0.00059061	0.00191669
BTW ($\hat{\beta}_T$)	500	0.00097687	0.00025901	0.00043548	0.00207420
BC ($\hat{\beta}_C$)	500	0.00160050	0.00123077	0.00085301	0.00291324
----- PCPN=1 N=90 -----					
ALN ($\hat{\alpha}_U$)	500	-2.83993113	133.15607358	-2959.97601727	247.70722155
AMLE ($\hat{\alpha}_{MLE}$)	210	1.94615422	0.34104616	1.15804507	3.18288250
ATW ($\hat{\alpha}_T$)	500	2.11797467	0.49548865	1.12144317	3.68745836
AC ($\hat{\alpha}_C$)	500	1.35666222	0.31540550	0.13357897	2.26403213
BUN ($\hat{\beta}_U$)	500	0.00093754	0.00124449	-0.00067556	0.00215448
BMLE ($\hat{\beta}_{MLE}$)	210	0.00107136	0.00019934	0.00064014	0.00159667
BTW ($\hat{\beta}_T$)	500	0.00099167	0.00024665	0.00048652	0.00185903
BC ($\hat{\beta}_C$)	500	0.00164163	0.00131164	0.00075390	0.00289578
----- PCPN=1 N=100 -----					
ALN ($\hat{\alpha}_U$)	500	1.63492874	11.56378955	-129.03171368	72.73812809
AMLE ($\hat{\alpha}_{MLE}$)	195	1.96347302	0.34103539	1.20916636	3.40118556
ATW ($\hat{\alpha}_T$)	500	2.13292721	0.49384102	0.97690597	4.54784515
AC ($\hat{\alpha}_C$)	500	1.36234510	0.31543719	0.16316701	2.33434227
BUN ($\hat{\beta}_U$)	500	0.00091653	0.00129708	-0.00106843	0.00162225
BMLE ($\hat{\beta}_{MLE}$)	195	0.00104741	0.00018389	0.00054983	0.00153527
BTW ($\hat{\beta}_T$)	500	0.00098237	0.00024817	0.00037344	0.00215046
BC ($\hat{\beta}_C$)	500	0.00164413	0.00130765	0.00080834	0.00172765

Table 4.1.2 (cont.)

						PCPN=2	N=10
VARIABLE		N	MEAN	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE	
ALN	($\hat{\alpha}_u$)	500	2.67240299	16.47586608	-73.70930344	125.66401844	
AMLE	($\hat{\alpha}_{MLE}$)	331	2.74919700	2.24016790	0.41753031	18.56444747	
ATW	($\hat{\alpha}_T$)	500	7.57701804	20.09302921	-24.68177198	289.93515789	
AC	($\hat{\alpha}_c$)	500	1.42074804	1.13977417	0.19772239	19.58776863	
BUN	($\hat{\beta}_u$)	500	-0.00064227	0.00843137	-0.09975146	0.01237043	
BMLE	($\hat{\beta}_{MLE}$)	381	0.00104654	0.00062476	0.00003495	0.00383732	
BTW	($\hat{\beta}_T$)	500	0.00067778	0.00058587	-0.00011771	0.00417362	
BC	($\hat{\beta}_c$)	500	0.00186041	0.00153123	0.00003719	0.01403740	
						PCPN=2	N=20
ALN	($\hat{\alpha}_u$)	500	-3.90707869	108.59959981	-2240.18308693	328.76701430	
AMLE	($\hat{\alpha}_{MLE}$)	328	2.26500146	1.08275913	0.87677253	10.59110818	
ATW	($\hat{\alpha}_T$)	500	3.39012449	3.38973428	0.41791478	41.87340826	
AC	($\hat{\alpha}_c$)	500	1.13468369	0.50217090	0.10345186	4.76171014	
BUN	($\hat{\beta}_u$)	500	-0.00026530	0.00697683	-0.05003494	0.06793155	
BMLE	($\hat{\beta}_{MLE}$)	328	0.00103431	0.00042118	0.00021350	0.00286962	
BTW	($\hat{\beta}_T$)	500	0.00075502	0.00049808	0.00003212	0.00308741	
BC	($\hat{\beta}_c$)	500	0.00244611	0.00434658	0.00049556	0.07460930	
						PCPN=2	N=30
ALN	($\hat{\alpha}_u$)	500	1.73334759	24.18215923	-226.19957624	334.46973295	
AMLE	($\hat{\alpha}_{MLE}$)	375	2.00023117	0.88383453	0.92594557	3.23637788	
ATW	($\hat{\alpha}_T$)	500	3.03237388	2.01287791	0.72280347	17.39169132	
AC	($\hat{\alpha}_c$)	500	1.07035986	0.39545110	0.08617075	2.90548079	
BUN	($\hat{\beta}_u$)	500	-0.00025827	0.00460251	-0.03456371	0.04291246	
BMLE	($\hat{\beta}_{MLE}$)	375	0.00110320	0.00034673	0.00022540	0.00239395	
BTW	($\hat{\beta}_T$)	500	0.00085050	0.00046519	0.00010525	0.00338379	
BC	($\hat{\beta}_c$)	500	0.00229261	0.00265270	0.00063056	0.04710504	
						PCPN=2	N=40
ALN	($\hat{\alpha}_u$)	500	2.94785615	29.81229066	-179.55587305	373.74358538	
AMLE	($\hat{\alpha}_{MLE}$)	360	1.98404040	0.55331186	0.84873664	4.54635117	
ATW	($\hat{\alpha}_T$)	500	2.66195436	1.29749324	0.68463362	9.49739372	
AC	($\hat{\alpha}_c$)	500	1.04570501	0.36161255	0.09466636	2.71769632	
BUN	($\hat{\beta}_u$)	500	0.00017560	0.00399585	-0.03033700	0.03475907	
BMLE	($\hat{\beta}_{MLE}$)	360	0.00110009	0.00032626	0.00041544	0.00291709	
BTW	($\hat{\beta}_T$)	500	0.00091051	0.00044112	0.00017459	0.00297385	
BC	($\hat{\beta}_c$)	500	0.00241033	0.00277974	0.00077683	0.03894991	
						PCPN=2	N=50
ALN	($\hat{\alpha}_u$)	500	5.45859236	91.64778091	-130.99287936	2017.82093735	
AMLE	($\hat{\alpha}_{MLE}$)	330	1.95463671	0.51001135	0.89757734	4.47302972	
ATW	($\hat{\alpha}_T$)	500	2.63485538	1.24019365	0.59829274	13.83034742	
AC	($\hat{\alpha}_c$)	500	1.01253606	0.34044151	0.08904025	2.32499252	
BUN	($\hat{\beta}_u$)	500	-0.00022950	0.00445794	-0.02349509	0.04785729	
BMLE	($\hat{\beta}_{MLE}$)	330	0.00108517	0.00028619	0.00041319	0.00285437	
BTW	($\hat{\beta}_T$)	500	0.00088602	0.00043546	0.00015375	0.00565953	
BC	($\hat{\beta}_c$)	500	0.00243133	0.00312078	0.00078018	0.05211494	

Table 4.1.2 (cont).

PCPN=2 N=60					
VARIABLE	N	MEAN	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
AUN ($\hat{\alpha}_u$)	500	-0.70207798	40.73474439	-429.47395779	496.86734632
AMLE ($\hat{\alpha}_{MLE}$)	288	1.91056051	0.44099009	1.05290069	3.74037729
ATW ($\hat{\alpha}_T$)	500	2.46876293	0.92336922	0.73423858	6.07325954
AC ($\hat{\alpha}_c$)	500	1.01287347	0.31891510	0.07064940	2.09756808
BUN ($\hat{\beta}_u$)	500	0.00003194	0.00432342	-0.01729585	0.05027137
BMLE ($\hat{\beta}_{MLE}$)	288	0.00110966	0.00025777	0.00049460	0.00208458
BTW ($\hat{\beta}_T$)	500	0.00092342	0.00039647	0.00024507	0.00350355
BC ($\hat{\beta}_c$)	500	0.00250394	0.00343556	0.00074040	0.05363724
----- PCPN=2 N=70 -----					
AUN ($\hat{\alpha}_u$)	500	0.32525361	37.96921741	-671.97467425	226.98107548
AMLE ($\hat{\alpha}_{MLE}$)	275	1.93360965	0.41190704	1.01083616	3.53242220
ATW ($\hat{\alpha}_T$)	0	.	.	.	.
AC ($\hat{\alpha}_c$)	500	0.97964273	0.28085205	0.07612608	1.84272779
BUN ($\hat{\beta}_u$)	500	-0.00006926	0.00390585	-0.01820543	0.04206101
BMLE ($\hat{\beta}_{MLE}$)	275	0.00108476	0.00024892	0.00048094	0.00190705
BTW ($\hat{\beta}_T$)	0	.	.	.	.
BC ($\hat{\beta}_c$)	500	0.00247184	0.00296271	0.00102729	0.04860958
----- PCPN=2 N=80 -----					
AUN ($\hat{\alpha}_u$)	500	-1.31025036	117.18061909	-1732.28297691	1669.77397294
AMLE ($\hat{\alpha}_{MLE}$)	251	1.92672903	0.40183824	1.13867107	3.34617159
ATW ($\hat{\alpha}_T$)	0	.	.	.	.
AC ($\hat{\alpha}_c$)	500	0.96151176	0.29209458	0.07377236	2.04593202
BUN ($\hat{\beta}_u$)	500	0.00005723	0.00370163	-0.01491859	0.03876876
BMLE ($\hat{\beta}_{MLE}$)	251	0.00109735	0.00024286	0.00059475	0.00184925
BTW ($\hat{\beta}_T$)	0	.	.	.	.
BC ($\hat{\beta}_c$)	500	0.00256122	0.00309321	0.00081028	0.04603445
----- PCPN=2 N=90 -----					
AUN ($\hat{\alpha}_u$)	500	0.79136739	17.10305637	-212.41874904	152.12301841
AMLE ($\hat{\alpha}_{MLE}$)	236	1.93972801	0.36821192	1.23509290	3.12548430
ATW ($\hat{\alpha}_T$)	0	.	.	.	.
AC ($\hat{\alpha}_c$)	500	0.96222123	0.29118987	0.06857482	1.76925460
BUN ($\hat{\beta}_u$)	500	0.00022749	0.00355566	-0.01141393	0.04031046
BMLE ($\hat{\beta}_{MLE}$)	236	0.00107807	0.00021394	0.00063213	0.00176903
BTW ($\hat{\beta}_T$)	0	.	.	.	.
BC ($\hat{\beta}_c$)	500	0.00260207	0.00303117	0.00095090	0.04464179
----- PCPN=2 N=100 -----					
AUN ($\hat{\alpha}_u$)	800	-27.31097817	538.30635596	-10744.0525210	402.02191508
AMLE ($\hat{\alpha}_{MLE}$)	335	1.92843721	0.36913159	1.2962321	3.23092133
ATW ($\hat{\alpha}_T$)	600	-17.72685534	439.67079275	-10744.0525210	44.91091698
AC ($\hat{\alpha}_c$)	800	0.94252753	0.27275381	0.0881537	1.64688011
BUN ($\hat{\beta}_u$)	800	0.00000578	0.00341113	-0.0147885	0.03301532
BMLE ($\hat{\beta}_{MLE}$)	335	0.00107845	0.00020111	0.0006256	0.00178264
BTW ($\hat{\beta}_T$)	600	1.13725436	1.22667378	0.0003746	4.65687376
BC ($\hat{\beta}_c$)	800	0.00258518	0.00271429	0.0011213	0.03924761

but the range of $\hat{\alpha}_u$ fluctuates. The distributions of the estimates appear in the histograms to become more concentrated around the true value as the sample size increases; however, the variance fluctuates in both populations. Table 4.1.2 gives summary statistics of all the estimates from every sample size and both populations. Since the negative values of $\hat{\alpha}_u$ and $\hat{\beta}_u$ are unacceptable they are omitted from the calculations of the means illustrated in Figures 4.1.7 to 4.1.10 and also from the statistics in Table 4.1.2. Table 4.1.3 is an ordered listing of $\hat{\alpha}_u$ from samples of size 100 from Population Two. The large number of negatives can be observed.

The empirical distributions of $\hat{\alpha}_u$ and $\hat{\beta}_u$ were tested for normality using SAS procedure Univariate. This procedure uses the Kolmogorov-Smirnov D statistic. In testing

H_0 : The estimates come from a normal (μ, σ^2) distribution vs

H_1 : The obvious alternative hypothesis

the hypothesis is rejected for large values of D. In every case, the null hypothesis of a normal distribution of $\hat{\alpha}_u$ and $\hat{\beta}_u$ was rejected. A shifted lognormal or a shifted gamma is suggested as a trial distribution for future study. It was expected that $\hat{\alpha}_u$ and $\hat{\beta}_u$ would show high correlation as had been observed in [1]. However, Figures 4.1.11 and 4.1.12 show little correlation between $\hat{\alpha}_u$ and $\hat{\beta}_u$.

4.2 Time-Weighted Method-of-Moments Estimators

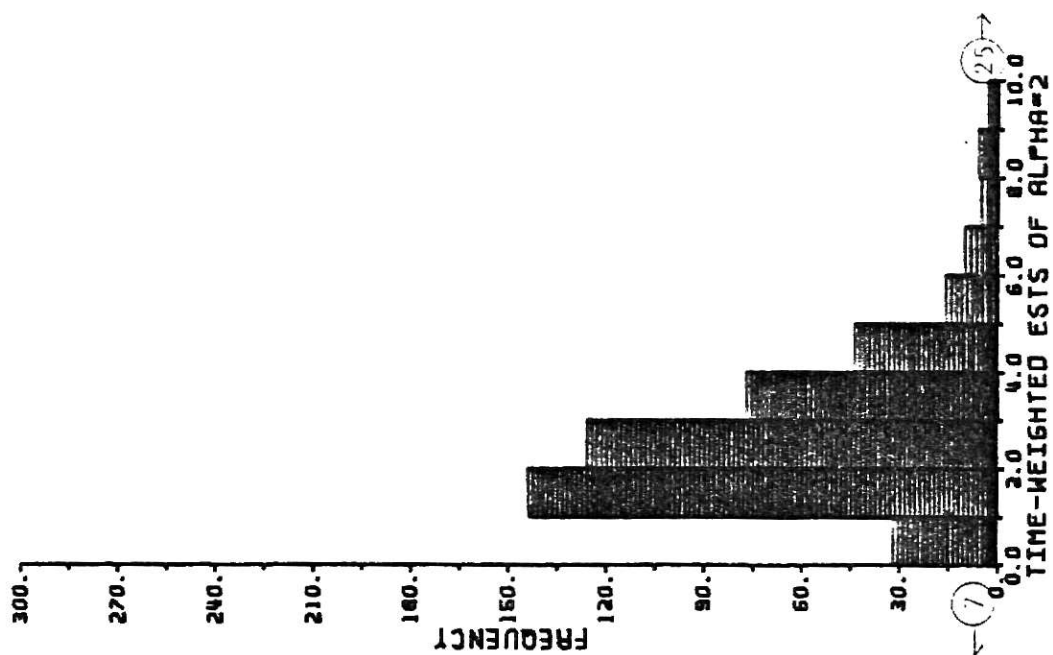
The time-weighted method-of-moments estimators behaved less erratically than the unweighted method-of-moments estimators. This was unexpected for at least two reasons. According to the Bayesian philosophy it should not be desirable to weight the estimates of λ_i by the experiment times. It can be argued that nature chooses the values of λ_i for each experiment. Therefore,

each is as important as the next and the estimate $\hat{\lambda}_1$ from a short experiment is as valuable to a statistician as an estimate $\hat{\lambda}_1$ from a long experiment. Additionally, it has been demonstrated by Grosh [2] that the $\bar{\lambda}_u$ usually have smaller variance than the $\bar{\lambda}_T$, and hence it could be expected that $\hat{\alpha}_u$ and $\hat{\beta}_u$ would have smaller variances than $\hat{\alpha}_T$ and $\hat{\beta}_T$. In spite of this, the simulation results showed the time-weighted estimators to be better in several respects than the unweighted estimators. The sample variances of the values obtained by $\hat{\alpha}_T$ and $\hat{\beta}_T$ generally decreased as the sample size increased in both populations while the range fluctuated. The variances were less for the time-weighted method-of-moments estimates than for the unweighted method-of-moments estimates in every case except when estimating α from samples of size ten. Table 4.1.2 documents these results. Also note that the sample variance was smaller for estimates of α from Population One than for Population Two and larger for estimates of β .

The time-weighted method-of-moments estimator did not produce such a discouraging number of negative values. In fact, although it can take on those unsatisfactory values, none were observed for samples of size twenty or more. Figures 4.2.1 to 4.2.6 show the histograms of the values obtained by $\hat{\alpha}_T$ and $\hat{\beta}_T$ in Population One and Population Two for samples of size 10, 50 and 100. The tendency of the estimates to cluster more and more toward the true value is apparent as the sample size increases.

Figures 4.1.7 to 4.1.10 illustrate the means of the 500 estimates $\hat{\alpha}_T$ and $\hat{\beta}_T$ drawn from each of the sample sizes. The time-weighted method-of-moments estimators are clearly biased. The bias tends toward zero as the sample size increased in both populations. The correlation between $\hat{\alpha}_u$ and $\hat{\beta}_u$ increased in a negative direction as the sample size increased. Figures 4.1.11 and 4.1.12 illustrate this fact. Recalling that the gamma distribution

POPULATION ONE N=10



POPULATION TWO N=10

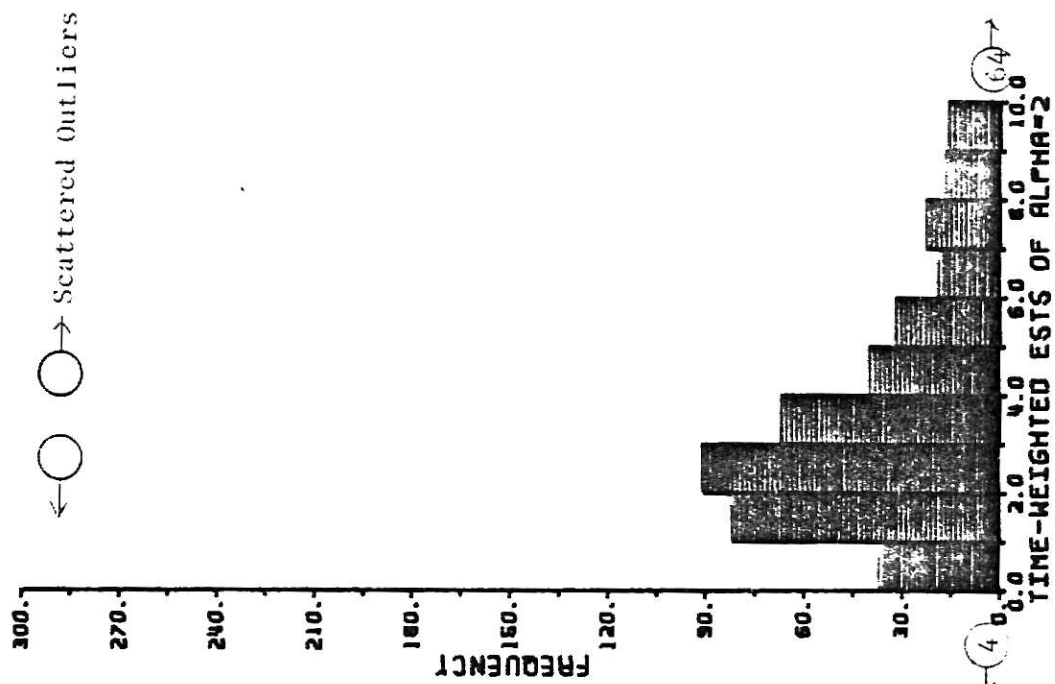


Figure 4.2.1

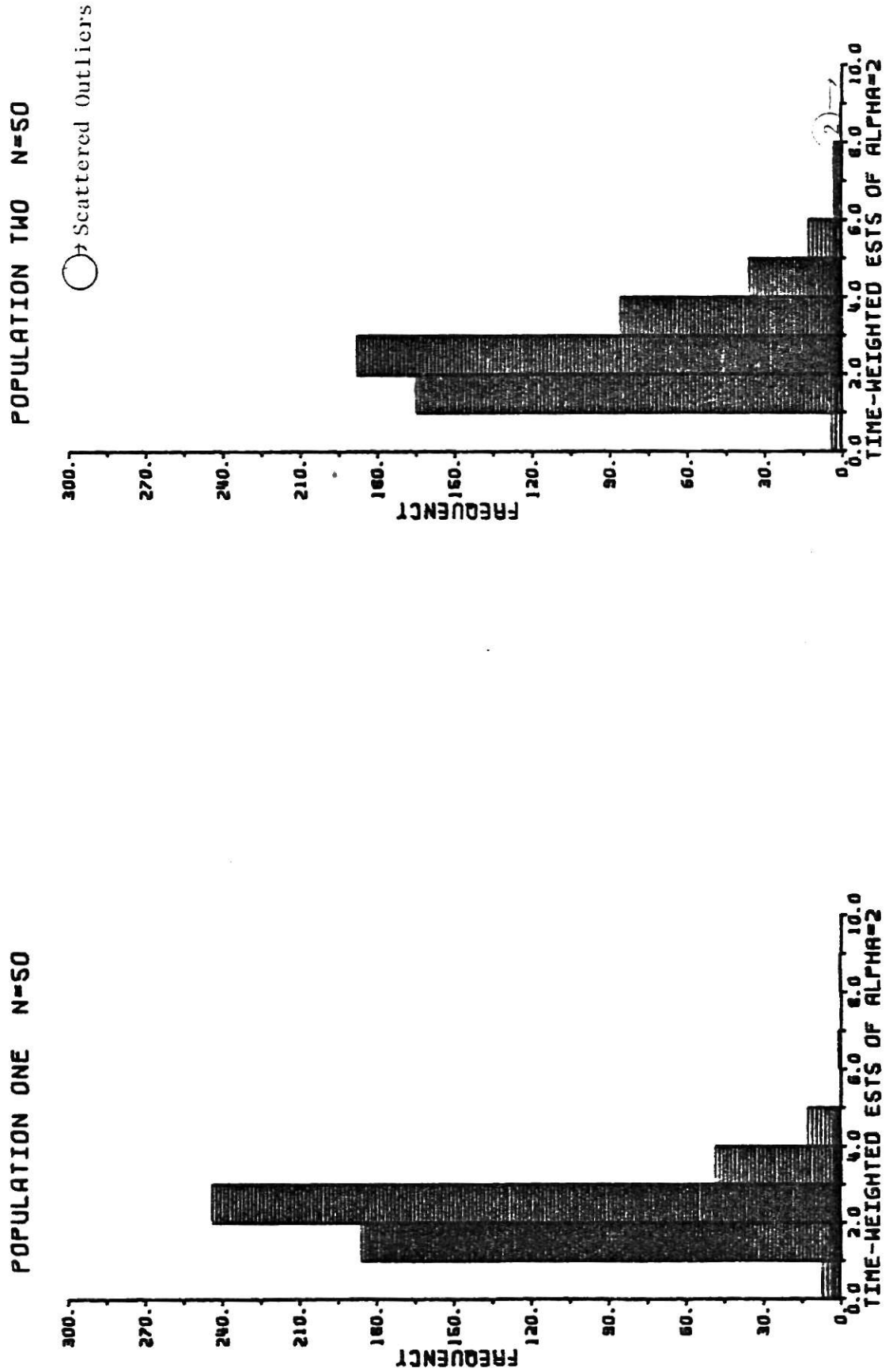


Figure 4.2.2

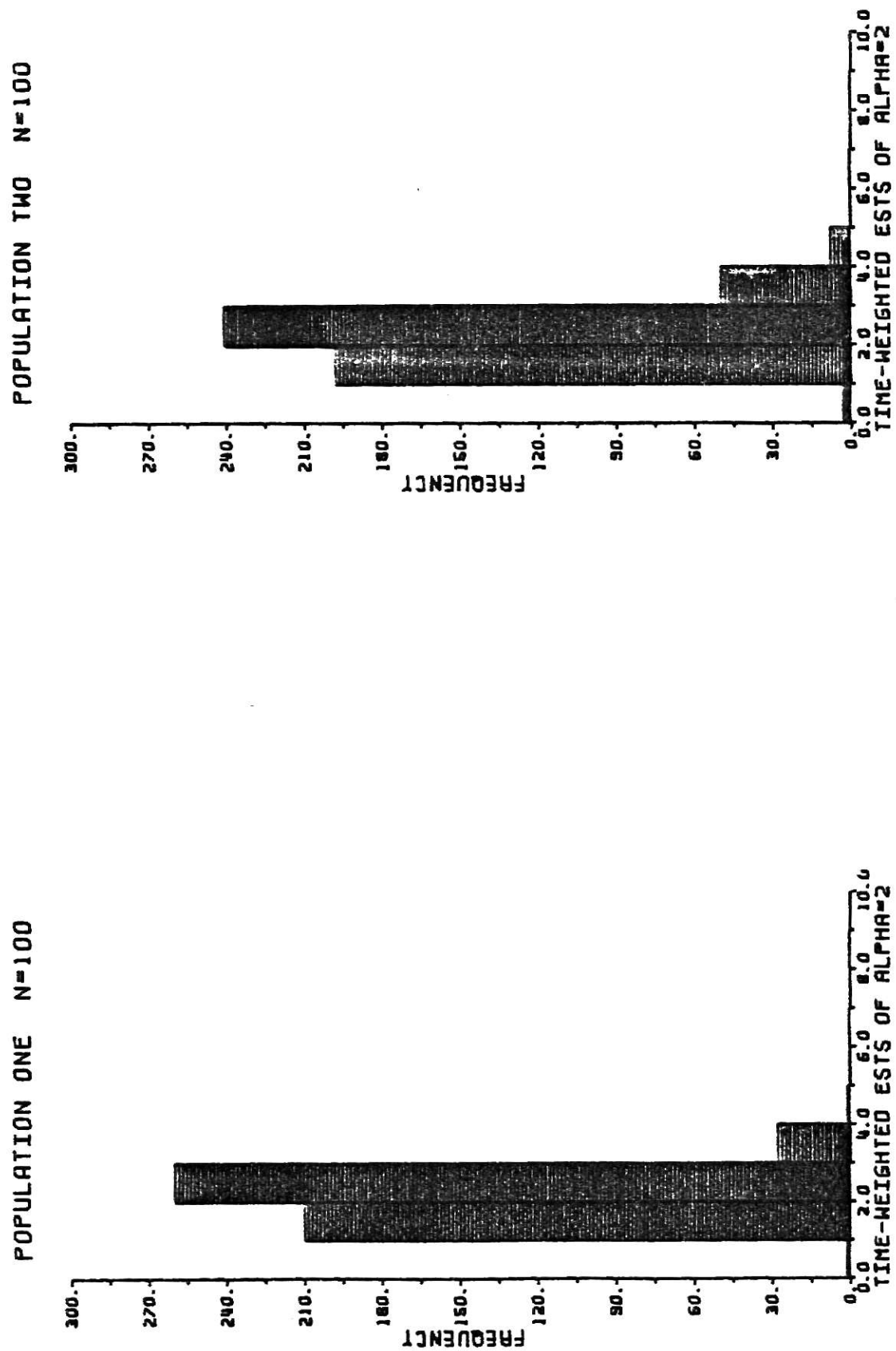


Figure 4.2.3

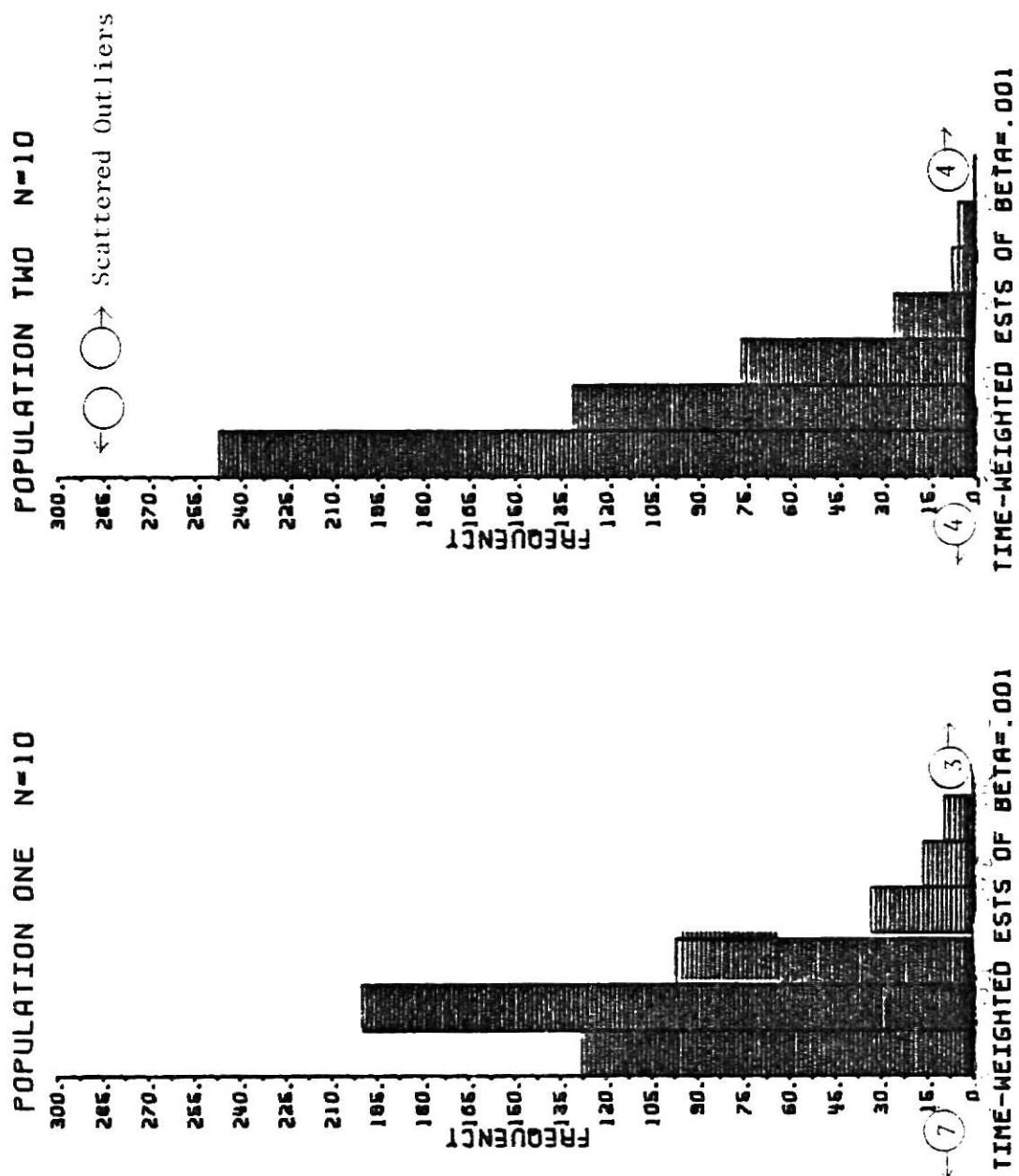


Figure 4.2.4

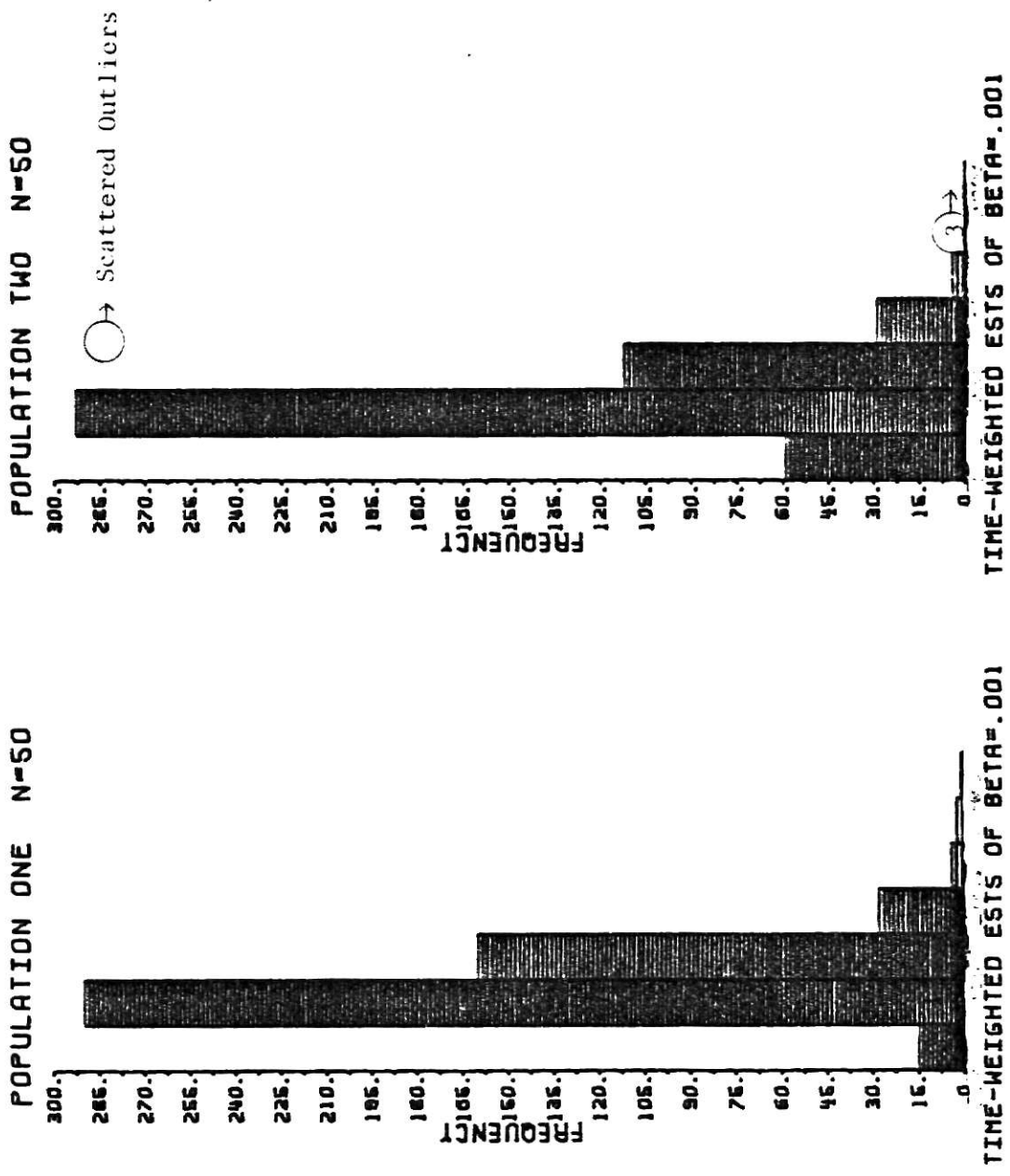


Figure 4.2.5

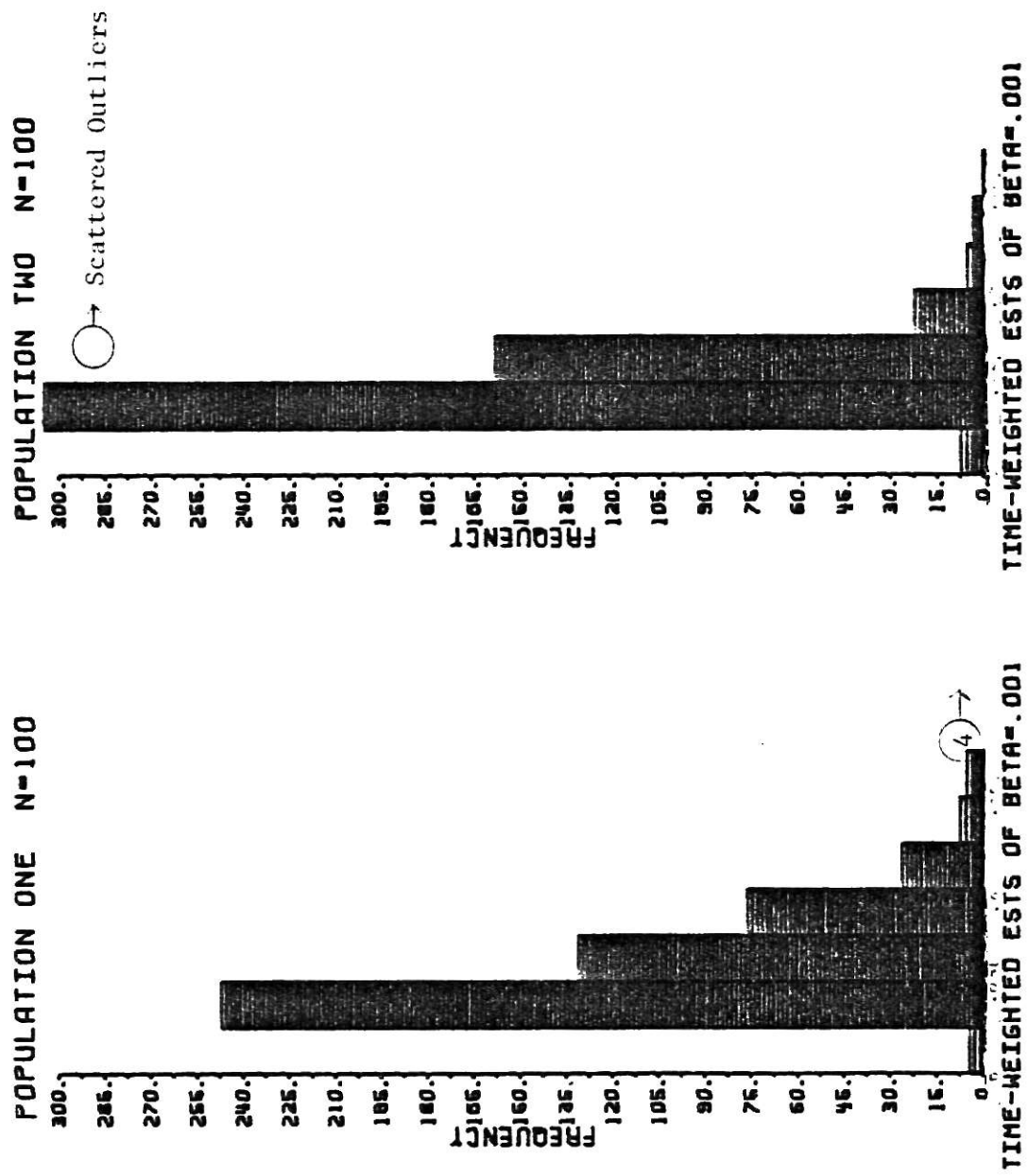


Figure 4.2.6

has $E(\lambda) = \alpha\beta$, we expected $\hat{\alpha}$ or $\hat{\beta}$ to decrease as the other increases so the negative correlation was expected.

4.3 Maximum Likelihood Estimators

The maximum likelihood estimators cannot produce any negative values since the Newton-Raphson procedure used in this study is constrained to positive values only (see Section 6: Documentation for details used in programming the Newton-Raphson procedure).

Figures 4.3.1 to 4.3.6 show the comparison of the histograms of $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$. As the sample size increased the histograms became narrower and more spiked in the vicinity of the true values, $\alpha = 2$ and $\beta = .001$. The ranges of $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$ were dramatically smaller than the ranges of $\hat{\alpha}_u$ and $\hat{\beta}_u$ and noticeably narrower than those of $\hat{\alpha}_T$ and $\hat{\beta}_T$.

Table 4.3.1 is an ordered list of $\hat{\beta}_{MLE}$ for samples of size 50 from Population One. This shows the narrow range and also illustrates the major difficulty of the maximum likelihood estimators. For economy the Newton-Raphson procedure was limited in this study to twenty iterations. If the Newton-Raphson procedure did not converge within the twenty allowed iterations, it was denoted by $\hat{\alpha}_{MLE} = \hat{\beta}_{MLE} = '.'$. SAS treats '.' as a missing value, and it was ignored in calculations of the statistics summarized in Table 4.1.2.

The ranges and variances of the $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$ generally decreased as the sample size increased, and both are less for Population One than for Population Two. The means of $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$ are plotted in Figures 4.1.7 to 4.1.10. As the sample size increases the means of the maximum likelihood estimates began poorly, tended toward the parameter value and then "overshot" it. It is possible that the means may be beginning a trend back to the true values, but larger samples would need to be simulated to investigate this behavior further. A possible explanation of this odd behavior is the

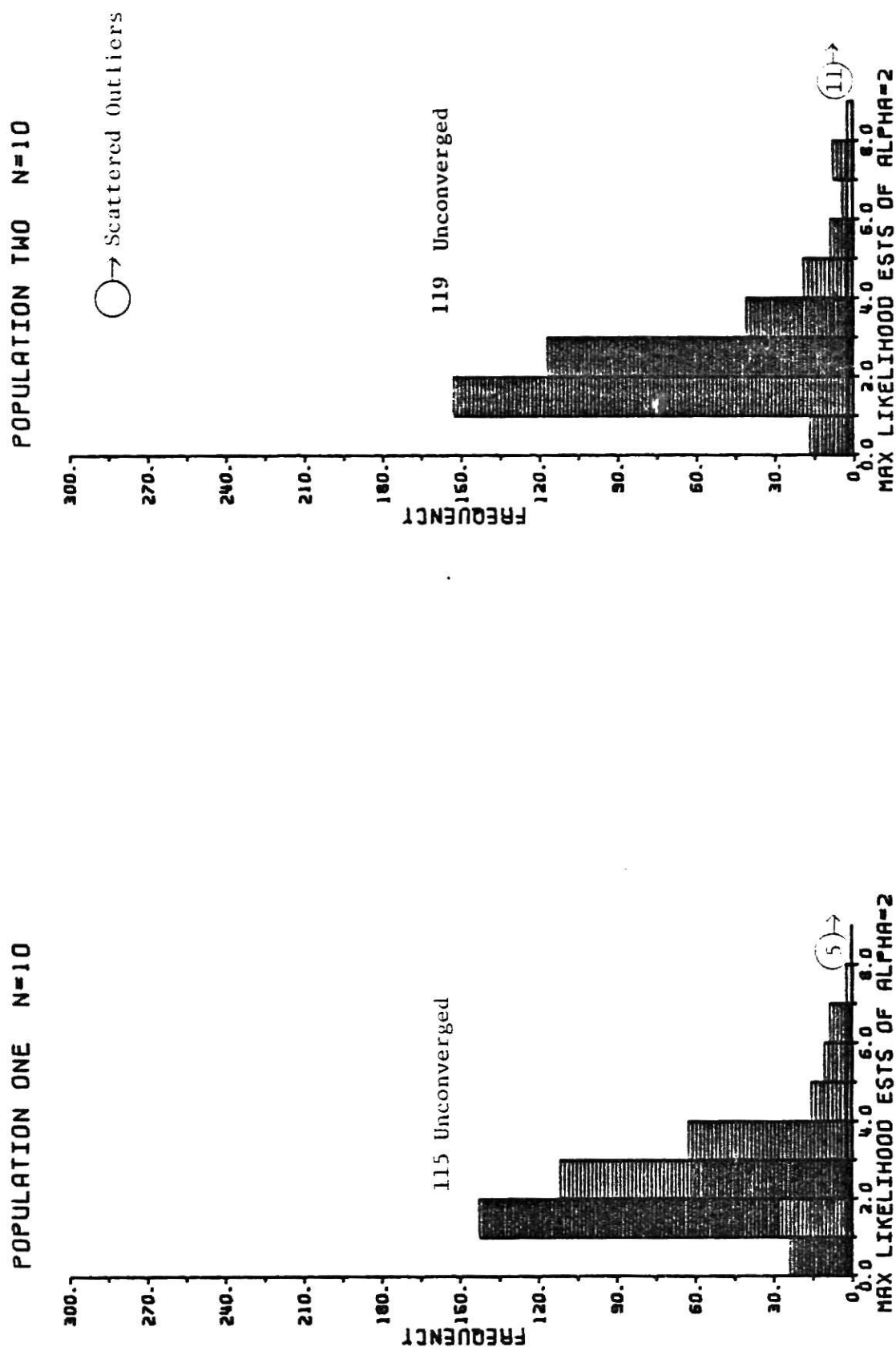


Figure 4.3.1

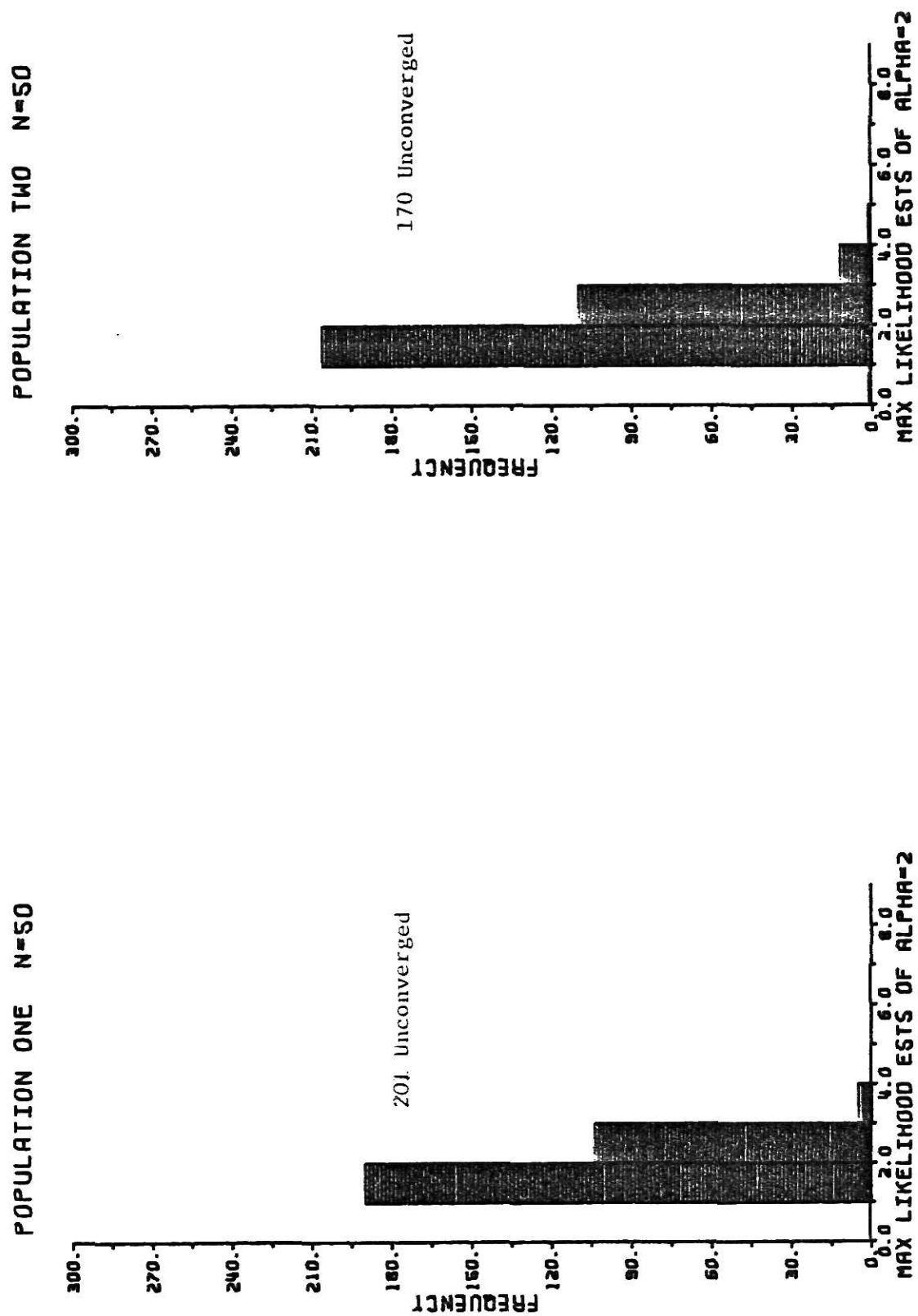


Figure 4.3.2

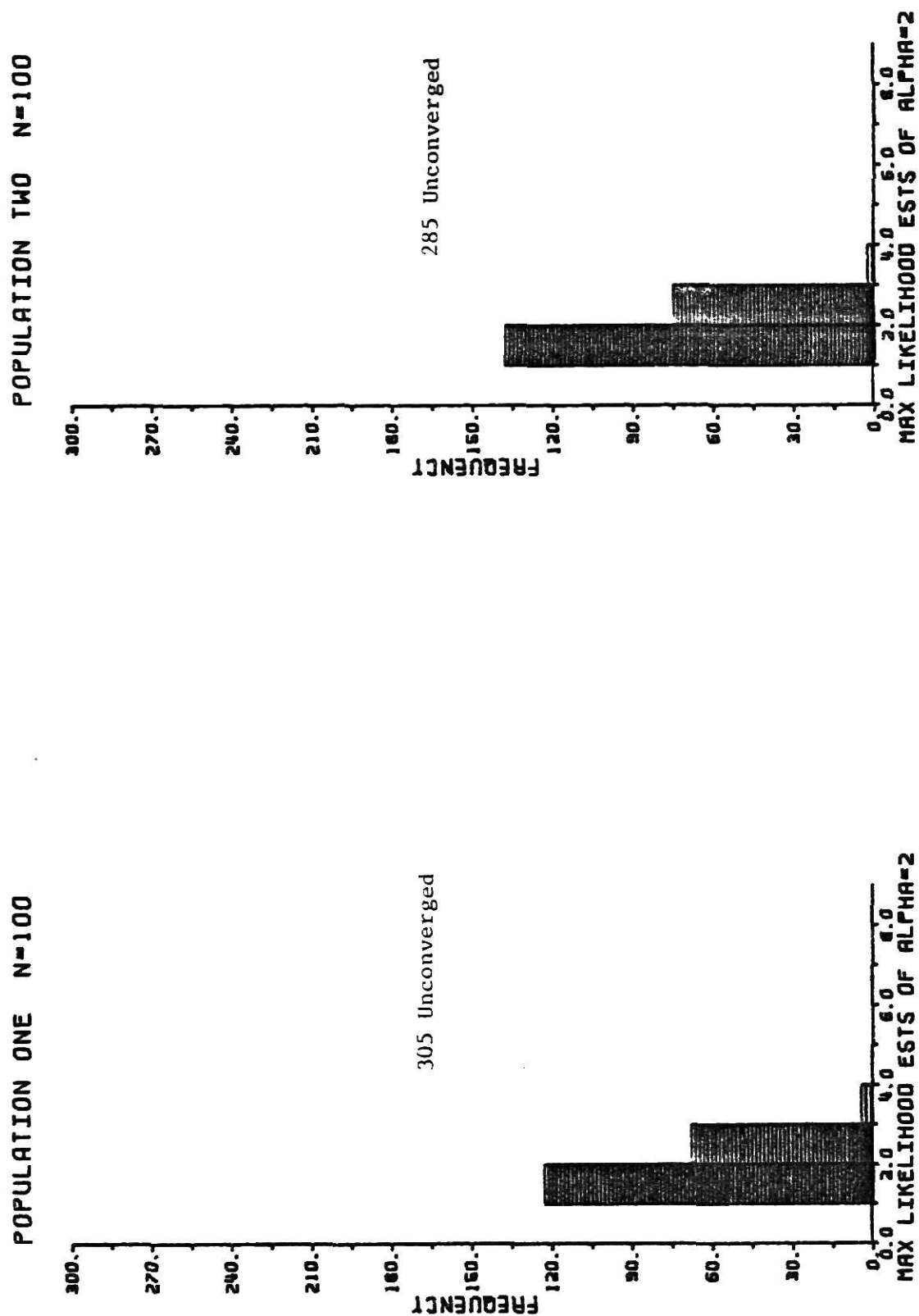


Figure 4.3.3

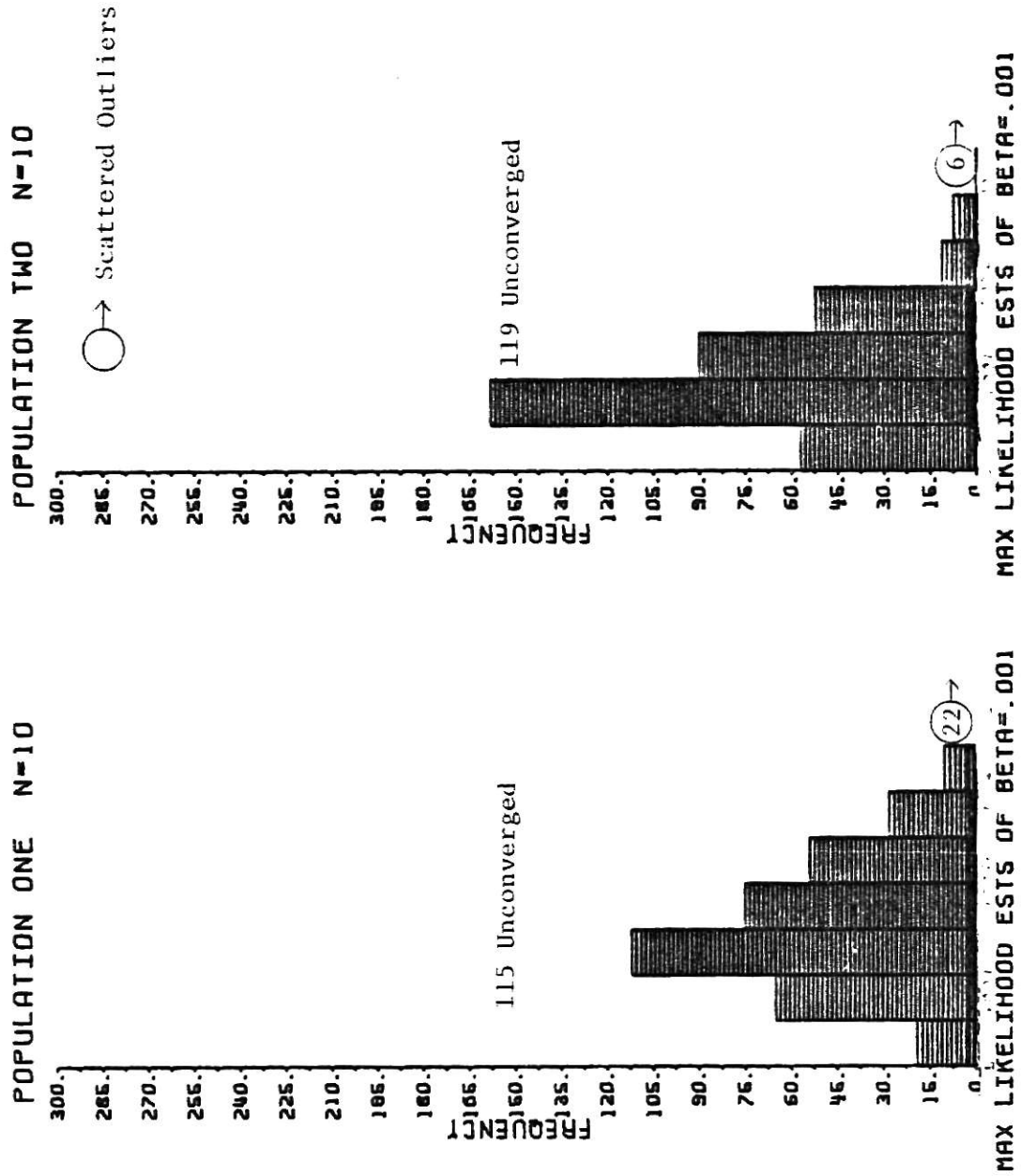


Figure 4.3.4

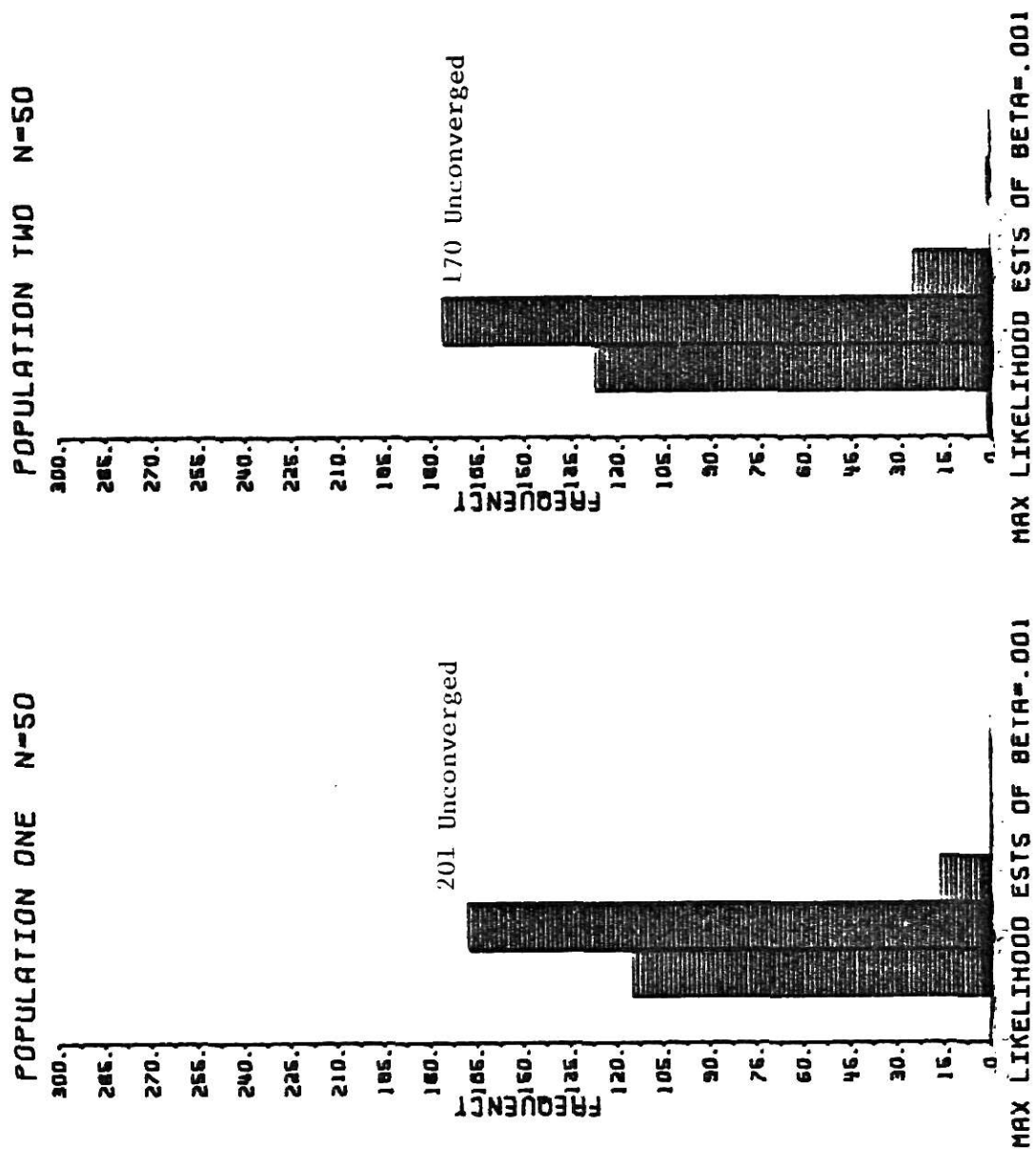


Figure 4.3.5

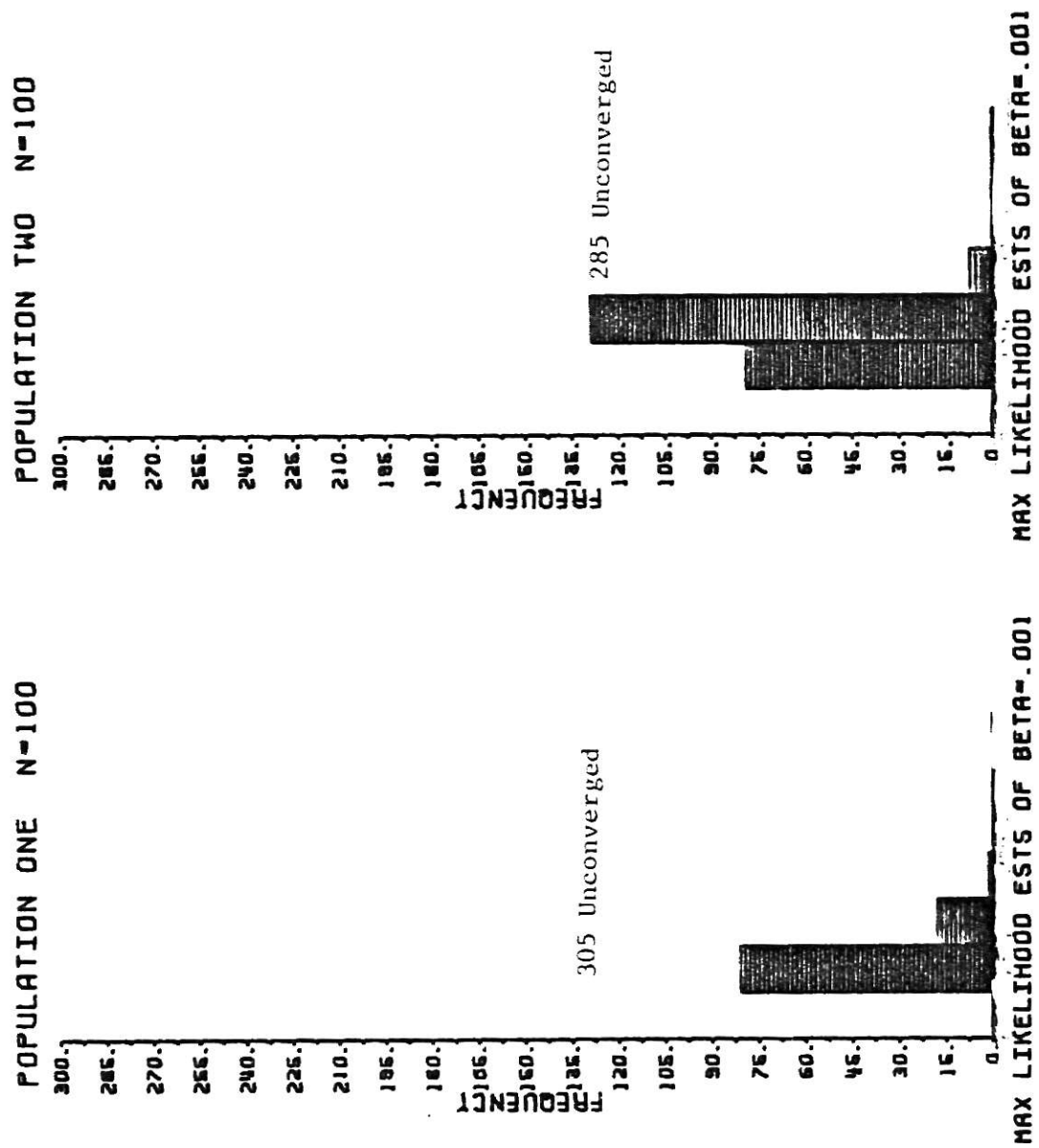


Figure 4.3.6

number of unconverged estimates. The values which the maximum likelihood estimators for these samples would eventually attain if the Newton-Raphson procedure were continued through enough iterations might effect the means. It was expected that the means would show a bias which would tend toward zero for large sample sizes.

More samples from Population One than from Population Two yielded maximum likelihood estimates, except when using samples of size ten. The Newton-Raphson procedure is sensitive to the starting value used and this may contribute to the larger number of unconverged maximum likelihood estimates for larger sample sizes. Recall (from 2.4) that the means of the matching-moments-to-the-prior estimates drifted away from the true values as the sample size increased. This value was used as a starting value and that may serve to explain the decreased number of maximum likelihood estimates in the large sample sizes. The unweighted and time-weighted method-of-moments estimates were tried as starting values for samples of size ten from Population One. The resulting number of unconverged maximum likelihood estimates was roughly twice the number observed when the matching-moments-to-the-prior estimates were used. The number of converged maximum likelihood estimates may increase greatly for the larger sample sizes if another estimate is used as a starting value, thus regaining the lost information from the small sample size. This possibility was not checked.

It was noticed that when ordering the unweighted and time-weighted method-of-moments estimates that the samples which yielded extreme values often also had unconverged maximum likelihood estimates. A Chi-squared test of independence was run to check this tendency. The unweighted method-of-moments estimators were classified as negative or non-negative, and the maximum likelihood estimators were classified as converged or unconverged. The hypothesis:

H_0 : $\hat{\alpha}_u$ and $\hat{\beta}_u$ (classified as above) are independent of $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$ (classified as above), vs

H_1 : not independent

was rejected five of ten times in Population One, and seven of ten times in Population Two. These tests looked only at one end of the scale in which the unweighted method-of-moments estimators could obtain extreme values, but they seem to indicate a relationship between the "bad" estimates from the different types of estimators. Since only samples of size ten produced negative time-weighted method-of-moments estimates the Chi-squared test was not run using $\hat{\alpha}_T$ and $\hat{\beta}_T$ with $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$.

It was desired to find the economic feasibility of the maximum likelihood estimators compared with the two method-of-moments estimators. Five hundred samples of size ten from Population One were run once including the calculations of the maximum likelihood estimates and once excluding them. That showed the maximum likelihood estimators to be quite expensive in comparison. The program with the maximum likelihood estimates ran in 42.57 seconds while it ran in 5.00 seconds without the maximum likelihood estimates. Cost also increased sharply as the number of iterations of the Newton-Raphson procedure increased. Thus we see the cost of computing many maximum likelihood estimates is high, but need not deter the experimenter with only a few data sets from which he wants estimates of α and β .

The empirical distributions of $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$ were tested for normality. In both populations samples of size 50 or more and Population One sample size 40 showed the distribution $\hat{\beta}_{MLE}$ could be approximated by the normal distribution. Also the distributions of $\hat{\alpha}_{MLE}$ from sample size 80 from both populations were normal. It is well known that maximum likelihood estimators are asymptotically normally distributed under certain constraints.

The correlation between $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$ was significantly negative and increased with the sample size in both populations. Figures 4.1.11 and 4.1.12 illustrate the correlation. The correlation between $\hat{\alpha}_{MLE}$ and $\hat{\alpha}_{MLE}$ was slightly higher than that of $\hat{\alpha}_T$ and $\hat{\beta}_T$. This was especially true in Population Two.

SECTION 5: DOCUMENTATION

The purpose of this program is to simulate the failure count from a Poisson process whose failure rate has a specific prior distribution. The prior distribution is chosen so that $X \sim \text{Poisson}(\lambda T)$ and $\lambda \sim \text{gamma}(\alpha=2, \beta=.001)$. Recall from equation [1.3] that the marginal distribution can be written as

$$h(x|\alpha, \beta) = \binom{x+\alpha-1}{\alpha} \left(\frac{T'}{T+T'}\right)^\alpha \left(\frac{T}{T+T'}\right)^x$$

where $T' = \frac{1}{\beta}$.

Since α and β are fixed for the simulation we can generate an experiment time and simulate a failure count. These failure counts and times are used to compute the estimates.

The steps used to generate the experiment time are determined by which population is being generated. If we are interested in Population One then $\text{ICODE} = 1$. A random number U is generated from a uniform $(0,1)$ distribution, multiplied by 10,000 and the integer part of the product is the experiment time $\text{IT}(I)$. To generate Population Two we set $\text{ICODE} = 2$ and a second randomization is introduced. The random number U is generated. Instead of multiplying by 10,000 the multiplier is determined by another random number RM so that

$$\text{IT}(I) \text{ equals the integer part of } \begin{cases} U \times 1,000 & \text{if } \text{RM} < .3 \\ U \times 10,000 & \text{if } .3 \leq \text{RM} \leq .7 \\ U \times 100,000 & \text{if } .7 < \text{RM} \end{cases}$$

where $\text{RM} \sim \text{uniform}(0,1)$. If $\text{IT}(I)$ equals zero it is ignored and another U is generated to begin the process.

Having the experiment time, the probability of an arrival in the negative binomial marginal distribution is

$$P = \frac{T'}{T+T'} = \frac{1000}{IT(I)+1000} \quad .$$

We are ready to begin simulating the arrivals and failure counts. We count the number of failures until the α^{th} (in this case 2) arrival. The balance of needed arrivals is denoted IALBAL. Another random number R is generated from a uniform (0,1) distribution, and compared to P the probability of an arrival. If R is an arrival (i.e., $R \leq P$) then IALBAL is decreased by one. If R is a failure (i.e., $R > P$) then IX(I) the failure count is increased by one. When IALBAL equals zero IX(I) represents the simulated failure count in IT(I) hours. When experiments are simulated the failure counts and experiment times are used to estimate λ_i by $\hat{\lambda}_i = \frac{IX(I)}{IT(I)}$. This process is repeated N times for $N = 10, 20, 30, \dots, 100$. These N values of λ_i are averaged according to the procedures described in 2.1 Unweighted Averaging and 2.2 Time-Weighted Averaging, and the unweighted method-of-moments estimates, the time-weighted method-of-moments estimates and the matching-moments-to-the-prior estimates are computed as specified in equations [2.1.1], [2.1.2], [2.2.1], [2.2.2], [2.4.1] and [2.4.2]. The Newton-Raphson procedure follows and then the four types of estimates of α and β are recorded. This completes one sample of size N. The entire process is repeated until 500 samples of size N have been generated.

The Newton-Raphson procedure is an iterative approximation to the root(s) of one or more simultaneous equations. The two dimensional case is of interest in this study. Solutions α^* and β^* to $f(\alpha, \beta) = 0$ and $g(\alpha, \beta) = 0$ are desired such that $f(\alpha^*, \beta^*) = g(\alpha^*, \beta^*) = 0$. Using (α_0, β_0) as an initial expansion point, the first order Taylor series approximation to $f(\alpha, \beta) = 0$ and $g(\alpha, \beta) = 0$ are

$$[5.1] \quad f(\alpha, \beta) \approx f(\alpha_0, \beta_0) + \left(\frac{\partial f}{\partial \alpha}\right)_0 (\alpha - \alpha_0) + \left(\frac{\partial f}{\partial \beta}\right)_0 (\beta - \beta_0) = 0$$

$$[5.2] \quad g(\alpha, \beta) \approx g(\alpha_0, \beta_0) + \left(\frac{\partial g}{\partial \alpha}\right)_0 (\alpha - \alpha_0) + \left(\frac{\partial g}{\partial \beta}\right)_0 (\beta - \beta_0) = 0$$

For ease of notation we let

$$f^0 = f(\alpha_0, \beta_0) \qquad g^0 = g(\alpha_0, \beta_0)$$

$$f_\alpha^0 = \left(\frac{\partial f}{\partial \alpha}\right)_0 \qquad g_\beta^0 = g\left(\frac{\partial g}{\partial \alpha}\right)_0$$

$$f_\beta^0 = \left(\frac{\partial f}{\partial \beta}\right)_0 \qquad g_\alpha^0 = g\left(\frac{\partial g}{\partial \beta}\right)_0$$

In matrix notation equations [5.1] and [5.2] can be written as

$$[5.3] \quad \begin{bmatrix} f^0 \\ g^0 \end{bmatrix} + \begin{bmatrix} f_\alpha^0 & f_\beta^0 \\ g_\alpha^0 & g_\beta^0 \end{bmatrix} \begin{bmatrix} \alpha - \alpha_0 \\ \beta - \beta_0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Solving for (α, β)

$$[5.4] \quad \begin{bmatrix} \alpha_1 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \beta_0 \end{bmatrix} - \begin{bmatrix} f_\alpha^0 & f_\beta^0 \\ g_\alpha^0 & g_\beta^0 \end{bmatrix}^{-1} \begin{bmatrix} f^0 \\ g^0 \end{bmatrix}$$

where α_1 and β_1 are improved estimates of α^* and β^* . This procedure is continued interactively replacing (α_i, β_i) with $(\alpha_{i+1}, \beta_{i+1})$ until $|f(\alpha_{i+1}, \beta_{i+1})| < \varepsilon$ and $|g(\alpha_{i+1}, \beta_{i+1})| < \varepsilon$ for a sufficiently small ε .

The likelihood equations from equations [2.3.3] and [2.3.4] are

$$f = \sum_{i=1}^n \sum_{z=1}^{x_i} \frac{1}{\alpha + z - 1} - \sum_{i=1}^n \ln(1 + \beta T_i) = \text{SUMF1} - \text{SUMF2}$$

$$g = \frac{\sum_{i=1}^n x_i}{\beta} = \sum_{i=1}^n \frac{(x_i + \alpha) T_i}{1 + \beta T_i} = \text{SUMG1} - \text{SUMG2}$$

The derivatives of the likelihood equations are

$$f_{\alpha}^0 = \sum_{i=1}^n \sum_{z=1}^{x_i} \frac{-1}{(\alpha+z-1)^2} = AA$$

$$g_{\beta}^0 = \frac{\sum_{i=1}^n x_i}{\beta^2} + \sum_{i=1}^n \frac{(x_i + \alpha) T_i^2}{(1 + \beta T_i)^2} = CC$$

and

$$f_{\beta}^0 = g_{\alpha}^0 = \sum_{i=1}^n \frac{-T_i}{(1 + \beta T_i)} = BB$$

Then equation [5.4] becomes

$$\begin{aligned} \begin{bmatrix} \alpha_1 \\ \beta_1 \end{bmatrix} &= \begin{bmatrix} \alpha_0 \\ \beta_0 \end{bmatrix} - \frac{1}{(AA)(CC) - (BB)^2} \begin{bmatrix} CC & -BB \\ -BB & AA \end{bmatrix} \begin{bmatrix} f_{\alpha}^0 \\ g_{\beta}^0 \end{bmatrix} \\ &= \begin{bmatrix} \alpha_0 \\ \beta_0 \end{bmatrix} - \frac{1}{DET} \begin{bmatrix} CCf_{\alpha}^0 - BBg_{\beta}^0 \\ -BBf_{\alpha}^0 + AA g_{\beta}^0 \end{bmatrix} \end{aligned}$$

Hence

$$\alpha_1 = \alpha_0 - \frac{(CCf_{\alpha}^0 - BBg_{\beta}^0)}{DET} = \alpha_0 - Y1$$

$$\beta_1 = \beta_0 - \frac{(AAg_{\beta}^0 - BBf_{\alpha}^0)}{DET} = \beta_0 - Y2$$

The initial expansion point is taken as the matching-moments-to-the-prior estimate. The program tests for negative values using

```
IF(ALL.LE.0.)GO TO 715
```

```
IF(BE1-0.)715,715,725
```

If α_1 or β_1 is not a positive value then the program in step 715 reduces the step size by one-half, recomputes α_1 and β_1 and checks again for negative values. For positive values of α_1 and β_1 , $f(\alpha_1, \beta_1)$ and $g(\alpha_1, \beta_1)$ are computed and checked for convergence. If $|f(\alpha_1, \beta_1)|$ or $|g(\alpha_1, \beta_1)|$ is not less than ϵ , (EPSL = .01), and the maximum number of iterations MAITER=20 has not been reached then another iteration is carried out by returning to step 250 and using (α_1, β_1) as the new expansion point. If $|f(\alpha_1, \beta_1)| < \epsilon$ and $|g(\alpha_1, \beta_1)| < \epsilon$ or if twenty iterations have been completed then all estimates are recorded and another sample is generated. If MAITER is reached, we set AL=999.0 and BE=999.0 which is interpreted as a sample with unconverged maximum likelihood estimates.

Notation used in the program

$$AA = f_{\alpha}^0$$

$$AC = \hat{\alpha}_{mmp}$$

$$AL = \hat{\alpha}_{MLE}$$

$$AL1 = \alpha \text{ trial value after iteration step}$$

$$AUN = \hat{\alpha}_u$$

$$ATW = \hat{\alpha}_T$$

$$BB = f_{\beta}^0 = g_{\alpha}^0$$

$$BC = \hat{\beta}_{mmp}$$

$$BE = \hat{\beta}_{MLE}$$

$$BE1 = \beta \text{ trial value after iteration step}$$

$$BET1 = 1 + \beta T_1$$

$$BUN = \hat{\beta}_u$$

$$BTW = \hat{\beta}_T$$

$$CC = g_{\beta}^0$$

$$DET = \det \begin{bmatrix} AA & BB \\ BB & CC \end{bmatrix} = (AA)(CC) - (BB)^2$$

$$EPSL = \epsilon = .01$$

$$F = \frac{\partial L}{\partial \alpha}$$

$$G = \frac{\partial L}{\partial \beta}$$

$$H = \frac{1}{n} \sum_{i=1}^n \frac{1}{T_i} = \text{inverse harmonic mean of experiment times}$$

$$IA = \alpha = 2$$

IALBAL = number of arrivals still needed in an experiment

ICODE = designation of population

$$ISUMT = \sum_{i=1}^n T_i$$

$$ISUMX = \sum_{i=1}^n x_i$$

IT(I) = T_i one experiment time

IX(I) = x_i failure count for one experiment

$$LAMBDA = \hat{\lambda}_i$$

M = 500 = total samples of each sample size

MAITER = 20 = maximum iterations for Newton-Raphson procedure

N = sample size 10, 20, 30, ..., 100

P = probability of an arrival $\frac{T'}{T+T'}$

R = random event in negative binomial, either an arrival ($R \leq P$)
or a failure ($R > P$).

RM = random number determining multipliers in Population Two

SEED = seed value for "super duper" random number generator

$$SLL = \sum_{i=1}^n \hat{\lambda}_i^2$$

$$STL = \sum_{i=1}^n T_i \hat{\lambda}_i$$

$$STLL = \sum_{i=1}^n T_i \hat{\lambda}_i^2$$

$$STT = \sum_{i=1}^n T_i^2$$

$$SUMC2 = \sum_{i=1}^n \frac{(x_i + \alpha) T_i^2}{(1 + \beta T_i)^2}$$

$$SUMF1 = \sum_{i=1}^n \sum_{z=1}^{x_i} \frac{1}{(\alpha + z - 1)}$$

$$SUMF2 = \sum_{i=1}^n \ln(1 + \beta T_i)$$

$$SUMG1 = \frac{\sum_{i=1}^n x_i}{\beta}$$

$$SUMG2 = \sum_{i=1}^n \frac{(x_i + \alpha) T_i}{(1 + \beta T_i)}$$

$$SUMLAM = \sum_{i=1}^n \hat{\lambda}_i$$

$$TPRIME = T' = \frac{1}{\beta}$$

U = random number used in experiment time

$$UBARL = \bar{\lambda}_u$$

$$UVARL = S_{\bar{\lambda}_u}^2$$

$$WBARL = \bar{\lambda}_T$$

$$WVARL = S_{\bar{\lambda}_T}^2$$

$$Y1 = \frac{CCf^0 - BBg^0}{DET} = \text{increment (step size)}$$

$$Y2 = \frac{AAG^0 - BBf^0}{DET} = \text{increment (step size)}$$

COMPUTER PROGRAM

```

C
C
C      DIMENSION IX(100),IT(100)
C      REAL *8 LAMDA, SUMLAM, UVARL, SLL, UVARL, WVARL, P, TIL, TL, STIL, STL, WVARL
C      C, AUN, AWEI, RUN, RWEI, TRAR, H, AC, RC, AL, RE, SUMF1, SUMF2, SUMG1, SUMG2,
C      CAA, RR, CC, SUMC2, RET1, DET, F, G, Y1, Y2, AL1, EPSL
C
C      500 SAMPLES
C      M=500
C
C      MAXIMUM ITERATIONS FOR NEWTON-RAPHSON PROCEDURE
C      MAITER=20
C
C      EPSILON FOR N-R
C      EPSL=.01D0
C
C      ALPHA
C      IA=2
C
C      SEED VALUE FOR "SUPER-DUPER" RANDOM NUMBER GENERATOR
C      SEED=0
C      T1=1/RETA
C      TPRIME=1000.00
C
C      POPULATION ONE OR TWO
C      ICODE=1
C
C      SAMPLE SIZE (10, 20, 30, ..., 100)
C      N=10
C
C      SET ALPHA BALANCE = ALPHA
C      IALBAL=IA
C
C      BEGIN 500 SAMPLES
C      DO 999 K=1,M
C
C          INITIALIZE SUMS
C          ISUMX=0
C          SLL=0
C          ISUMT=0
C          STT=0
C          SUMLAM=0
C          STIL=0
C          STL=0
C          H=0
C
C      GENERATE N EXPERIMENTS
C      DO 998 I=1,N
C
C          INITIALIZE FAILURE COUNT FOR THE EXPERIMENT
C          IX(I)=0
C
C      GENERATE EXPERIMENT TIME
C
C          RANDOM NUMBER FOR EXPERIMENT TIME
C          7 U=UNI(SEED)
C
C          IF TIME = 0 GET ANOTHER TIME
C          IF(U.LT..0000000000)GO TO 7
C
C          IF POPULATION ONE, TIME = U*10000
C          IF(ICODE.EQ.1)GO TO 5
C
C          IF POPULATION TWO, DO SECOND RANDOMIZATION
C
C          TIME = U *      1000 IF RM < .3
C                        10000 IF .3 <= RM <= .7
C                        100000 IF .7 < RM
C
C          WHERE RM IS A RANDOM NUMBER BETWEEN 0 AND 1

```

```

RM=UNI(SEED+2)
IF(RM.LT..3)GO TO 3
IF(RM.GT..7)GO TO 4
GO TO 5
3 IT(I)=INT(U*1000)
GO TO 6
4 IT(I)=INT(U*100000)
GO TO 6
5 IT(I)=INT(U*10000)

      PROBABILITY OF SUCCESS IN THE NEGATIVE BINOMIAL DISTRIBUTION IS
       $P = T'/(T + T')$ 
6 P=TPRIME/(IT(I)+TPRIME)

      INVERSE HARMONIC MEAN OF TIMES IS  $(1/N)*(SUM(1/T))$ 
       $H=H+(1/(N*DFLOAT(IT(I))))$ 

ONE EXPERIMENT

      GENERATE A RANDOM NUMBER, CHECK IT AGAINST P. IF IT IS A SUCCESS,
      (LESS THAN P) THEN REDUCE ALPHA BALANCE BY ONE. IF IT IS A
      FAILURE, INCREASE THE FAILURE COUNT BY ONE. IF IT IS A
      REPEAT UNTIL ALPHA SUCCESSES
100 R=UNI(SEED+1)
    IF (R.LE.P) GO TO 500
    IX(I)=IX(I)+1
    GO TO 100
500 IALRAL=IALRAL-1
    IF (IALRAL.EQ.0) GO TO 800
    GO TO 100

      CALCULATE LAMBDA HAT FOR THE EXPERIMENT
800 LAMBDA=DFLOAT(IX(I))/DFLOAT(IT(I))

      VALUES INVOLVED IN CALCULATING ESTIMATES OF ALPHA AND BETA
      ISUMX=ISUMX+IX(I)
      ISUMT=ISUMT+IT(I)
      SUMLAM=SUMLAM+LAMBDA
      SLL=SLL+LAMBDA**2
      STLL=STLL+DFLOAT(IT(I))*LAMBDA**2
      STL=STL+DFLOAT(IT(I))*LAMBDA
      STT=STT+IT(I)*IT(I)

      REINITIALIZE ALPHA BALANCE
      IALRAL=IA

      BACK TO NEXT EXPERIMENT
998 CONTINUE

UNWEIGHTED AND TIME WEIGHTED AVERAGES

UBARL=SUMLAM/N
TRAR=DFLOAT(ISUMT)/DFLOAT(N)
UVARL=(SLL-(SUMLAM**2)/N)/(N-1.)
WRARL=DFLOAT(ISUMX)/DFLOAT(ISUMT)
WVARL=(STLL-2.*WRARL*STL+WRARL**2*ISUMT)/DFLOAT(ISUMT)

UNWEIGHTED METHOD OF MOMENTS
13 AUN=UBARL**2/(UVARL-(WRARL**2))
   BUN=(UVARL/UBARL)-H

TIME WEIGHTED METHOD OF MOMENTS
ATW=(WRARL**2)*C/(WVARL-(WRARL*DFLOAT(N-1)/DFLOAT(ISUMT)))
BTW=((WVARL/WRARL)-DFLOAT(N-1)/DFLOAT(ISUMT))/C

```

```

C      MATCHING MOMENTS WITH THE PRIOR
C      AC=(U*VAR1**2)/U*VAR1
C      BC=U*VAR1/UR*ARL
C
C      MAXIMUM LIKELIHOOD ESTIMATION USING NEWTON-RAPHSON PROCEDURE
C
C      STARTING VALUE FOR N-R
C      AL=AC
C      RE=AC
C
C      INITIALIZE ITERATION
C      NITER=0
C
C      INCREMENT ITERATION
250 NITER=NITER+1
C
C      INITIALIZE SUMS
C      SUMF1=0
C      AA=0
C      SUMF2=0
C      SUMG2=0
C      BB=0
C      SUMC2=0
C
C      CALCULATE THE LIKELIHOOD FUNCTIONS, F AND G
C
C      DO 350 I=1,N
C      RET1=1.+RE*IT(I)
C      J=IX(I)
C      IF(J.EQ.0)GO TO 450
C      DO 350 L=1,L
C      SUMF1=SUMF1+1./((AL+L-1.)
550 AA=AA-1./((AL+L-1.)**2)
450 SUMG2=SUMG2+(IX(I)+AL)*IT(I)/RET1
C      SUMF2=SUMF2+DLOG(RET1)
C      BB=BB-IT(I)/RET1
C      SUMC2=SUMC2+(IX(I)+AL)*((DFLOAT(IT(I))/RET1)**2)
350 CONTINUE
C      SUMG1=DFLOAT(I*SUMX)/RE
C      CC=DFLOAT(-I*SUMX)/RE**2+SUMC2
C      DET=AA*CC-BB**2
C      F=SUMF1-SUMF2
C      G=SUMG1-SUMG2
C
C      CHECK THE NUMBER OF ITERATIONS. IF BEYOND THE LIMIT SET MLE'S = 999.0
C      AND RECORD VALUES FOR ALL TYPES OF ESTIMATORS
C      IF(NITER.LE.MAITER)GO TO 650
C      AL=999.00
C      RE=999.00
C      GO TO 751
C
C      CHECK CONVERGENCE
C      IF CONVERGENCE RECORD ALL TYPES OF ESTS
650 IF(DABS(G)-EPSL)651,651,705
651 IF(DABS(F).LE.EPSL)GO TO 751
C
C      CALCULATE STEP SIZE
705 Y1=(1./DET)*(CC*F-BB*G)
C      Y2=(1./DET)*(BB*F-AA*G)
C
C      NEW ESTIMATES OF ALPHA AND BETA
710 AL=AL-Y1
C      BE=RE+Y2
C

```

```

C      CHECK FOR NEGATIVE VALUES. IF NEGATIVE REDUCE STEP SIZE AND CALCULATE
C      NEW ESTIMATES OF ALPHA AND BETA
      IF (AL1.LE.0.) GO TO 715
      IF (BE1.LE.0.) GO TO 715
715  Y1=0.5*Y1
      Y2=0.5*Y2
      GO TO 710

C      NEW STARTING VALUE FOR NEXT ITERATION
725  AL=AL1
      BE=BE1

C      RETURN FOR NEXT ITERATION
      GO TO 250
751  WRITE(RIK,N,ICODE,AIN,AWEI,AC,AL,BIN,BWEI,BC,BE

C      NEXT SAMPLE OF SIZE N
999  CONTINUE
      END
/*

```

REFERENCES

1. Grosh, D. L., "The Distribution of Method-of-Moments Estimators for Beta Parameters Based on a Simulation Study." Unpublished manuscript.
2. Grosh, D. L., "Marginal Distribution Estimators of the Gamma Prior Parameters for a Group of Poisson Processes." Unpublished manuscript.

COMPARISON OF ESTIMATORS FOR THE PARAMETERS OF THE
POISSON-GAMMA MARGINAL DISTRIBUTION

by

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B.S., University of Southern Colorado, 1977

AN ABSTRACT OF A MASTER'S REPORT

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Work began on this study when the Nuclear Regulatory Commission provided data consisting of failure counts and experiment times for pumps. This data could be considered to come from a Poisson process with failure rate λ where $\lambda \sim \text{gamma}(\alpha, \beta)$. The resulting marginal distribution is (for integer α) the negative binomial

$$h(x|\alpha, \beta) = \binom{\alpha+x-1}{\alpha} \left(\frac{T'}{T+T'}\right)^\alpha \left(\frac{T'}{T+T'}\right)^x I(x) \\ \{0, 1, 2, \dots\}$$

where $T' = \frac{1}{\beta}$.

Estimates of α and β were desired but no observations from the prior distribution were available since the λ_i were never observed, only estimated by $\hat{\lambda}_i = \frac{X_i}{T_i}$. The values which were observable were failure counts and experiment times, which were from the marginal distribution.

Four types of estimators of α and β , namely the unweighted method-of-moments estimators, the time-weighted method-of-moments estimators, the maximum likelihood estimators and the matching-moments-to-the-prior estimators were derived and compared. Lacking a large body of data, a simulation was done as a basis of comparison. Original plans included several values of α and β , however, cost of computing proved prohibitive, and all simulation was done with $\alpha = 2$ and $\beta = .001$.

The estimators were compared by histograms, means and bias, variance among the estimates and by correlation between $\hat{\alpha}$ and $\hat{\beta}$ of each type. The empirical distribution of every estimator was tested for normality, with only the maximum likelihood estimates fitting the normal distribution for sufficiently large sample sizes. Summary statistics for every estimator were also included.