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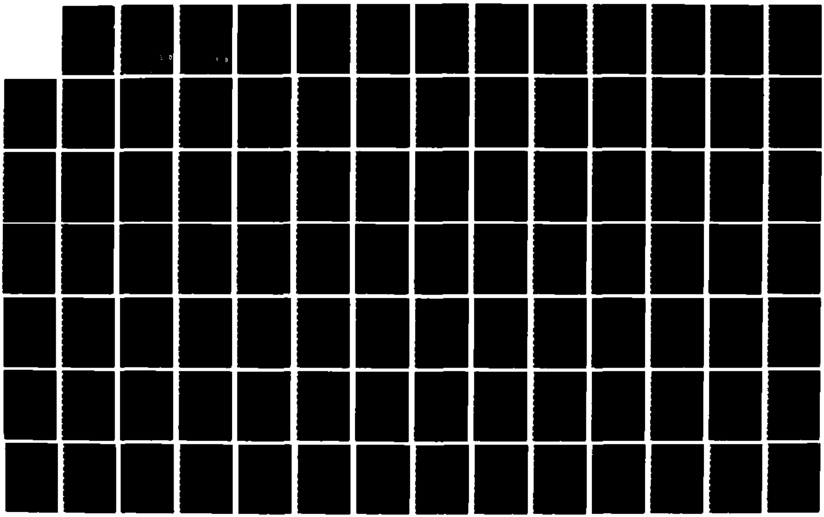

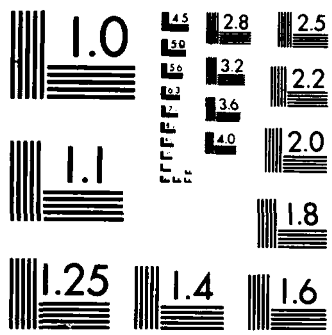

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NATIONAL BUREAU OF STANDARDS-1963-A

AD-A174 457

ERROR PREDICTIONS IN

ACCOUNTING POPULATIONS

THESIS

Blaine F. Webber
Captain, USAF

AFIT/GSM/LSY/86S-23

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ERROR PREDICTIONS IN ACCOUNTING POPULATIONS

THESIS

Presented to the Faculty of the School of Systems and Logistics

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the

Requirements for the Degree of

Master of Science in Systems Management

Blaine F. Webber, B.S.

Captain, USAF

September 1986

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ABSTRACT

The purpose of this ~~research~~ was to examine robustness, mean relative tightness, coverage, and power of selected unmodified and modified Cox and Snell and Stringer error limit bounds. The simulation was performed by repetitive sampling from an accounting population with various known book value and error distributions. Additional modifications to the selected modified Cox and Snell bounds was done by incrementally loosening the bounds by 5, 10, and 20 percent in a search for bounds with better performance characteristics.

There were several conclusions that could be made from this research. The modified Cox and Snell bounds can achieve high coverages for accounting populations with low error amount intensity (EAI) with significant increases in mean relative tightness over unmodified Cox and Snell bounds. The Stringer and Cox and Snell bounds can still achieve high coverages with significant improvements in mean relative tightness when the nominal confidence level is lowered from 90% to 85%. Only minor changes in prior probability settings materially affect the performance of Cox and Snell bounds. And, in accounting populations with low EAI, the selected Cox and Snell bounds are conservative.

ERROR PREDICTIONS IN ACCOUNTING POPULATIONS

I. Introduction

General Problem

Auditors are required to make statements about the accuracy of financial accounts by reviewing internal controls and empirical sampling. Through sampling and inferential statistics, auditors estimate as accurately as possible the maximum amount an account is likely to be in error. Their estimate is known as the upper error limit. The upper error limit is then compared to the material error, which is the limit of precision necessary for the account. Results of the comparison enable the auditor to state an opinion about the reasonable accuracy of the account (8:4,5).

> The estimation of upper error limits depends on our ability to construct models incorporating two aspects of accounting: the error rate and the distribution of error sizes for those accounts in error [3:180].

Traditionally, to reduce risk, auditors have chosen upper error limit bounds which result in very broad confidence intervals, possibly far in excess of the actual error. This conservative approach is due to the fact that little is known about the characteristics of accounting populations (7:270). Conservatism leads to possible erroneous rejection of the hypothesis that the book value of the audited population is reasonably accurate. Therefore, it is necessary to choose sampling plans and error limit bounds which are appropriate to the auditing situation.

Sampling should be done in such a way that a maximum amount of information can be obtained at a minimum cost.

> When the auditor samples accounting populations, he encounters two key sets of problems. One is connected with low error rates in the accounting populations. The other pertains to the effectiveness of sampling procedures designed for either low or high error rates when the actual error rates are not of the anticipated magnitude [10:4].

Low error rates pose significant problems for auditors who use classical statistical estimators. Dollar-unit sampling (DUS) was "specifically developed for use in the auditing environment where low error rates in account balances are often encountered" (3:179). Bayesian procedures using prior subjective information about accounting populations have been used DUS to produce tighter upper error limits than those obtained with the DUS method and classical estimators (3:179). The Bayesian approach, though, has its own problems: (1) difficulty in assessing a prior probability judgment, and (2) measurement of utility in those decisions where the sums involved are large (1:115).

Definition of Key Terms

Confidence Interval: the range around a calculated sample mean in which the population mean is expected to lie at the given confidence level.

Nominal Confidence Level: the expected frequency of correct intervals or bounds in repeated samples.

Conservatism: larger upper error limits calculated than the nominal confidence level.

Error Taint: the error amount found in a sample unit divided by the true book value.

Rel Tightness: the magnitude of an upper error limit relative to the true error in the population.

Coverage: in repetitive sampling, the percentage of calculated upper error limits which are equal to or greater than the true dollar error in the population.

Background

Upper Error Limits. When auditors first began using sampling techniques to estimate errors in accounting populations, they used classical sampling estimators: ratio and difference estimators.

> Stringer (1963) cautioned that use of these estimators entails potential dangers because their estimated standard errors will equal zero when no errors are found in the sample. With classical large-sample confidence limits this would imply that the point estimate of the total audit amount or the total error amount is perfect, which, obviously is not a reasonable conclusion in an audit situation employing a moderately large sample size [9:77].

To overcome the observed shortcomings with ratio and difference estimators, Stringer developed his own method of calculating error limits (called the Stringer bound). Although the Stringer bound has been used extensively, it is not without its own problems. First of all, no general theory has been published which supports the Stringer bound. This lack of theory occurs because the Stringer bound involves a combination of attributes and variables principles which makes theoretical analysis difficult. Second, the Stringer bound itself is very conservative, resulting in upper error limits far greater than the true error in populations (9:78).

In 1973, Anderson and Teitlebaum also identified potential dangers in using ratio and difference estimators for auditing when the error rate is small. They proposed using dollar-unit sampling together with the Stringer bound for estimating the total overstatement error in accounting populations. Dollar-unit sampling, which considers the individual dollar as the sample unit, requires no further stratification by book amount since all sampling units are exactly the same size in terms of book value without the need for stratification [8:78,79]. "Dollar-unit sampling can be thought of as employing the ultimate in stratification by book amount" [9:78].

In order to obtain more empirical evidence about the behavior of classical estimators, Neter and Loebbecke in 1975 conducted simulation studies with four actual accounting populations. They examined the performance of the mean-per-unit, ratio, and difference estimators each with simple, stratified random, and dollar-unit sampling. They found that, for the estimators under study, performance varied significantly depending upon the error sizes and the distribution of errors within the populations. When the population error rate was small to moderate or the distribution of errors was highly skewed, the actual proportions of correct confidence intervals was far below the nominal level. Even under the most favorable conditions, Neter and Loebbecke found that there is the possibility that the nominal confidence coefficient based on the normal distribution differs somewhat from the actual confidence level [10:134,135].

In 1977 Neter, Leitch, and Fienberg proposed a different method of obtaining a bound for total population error. Basing their bound on the multinomial probability distribution, they named it the multinomial bound for overstatement errors. The multinomial bound has been found to be effective because:

> (1) it incorporates information about the magnitude of the sample errors; (2) it has distributional properties which are fully known; and (3) it does not require any assumptions about the distribution of the population or of the errors in the population [5:3].

When used with dollar-unit sampling, the multinomial bound has been shown to be significantly tighter than the Stringer bound, with actual confidence levels nearer to nominal levels (5:3).

> While the use of monetary-unit sampling with either the Stringer bound or the multinomial bound avoids the problem of actual confidence levels far below the nominal level when there are few errors in an accounting population, neither the Stringer bound nor the multinomial bound permit a direct netting of

over- and understatement errors. Further, neither of these two bounds directly takes into account prior information which the auditor may have about the population error rate and/or the magnitude of the taintings in the population.

In contrast, a Bayesian approach to constructing bounds for the total error amount in an accounting population does enable the auditor to incorporate prior information into the estimation procedure, though there may be difficulties in making the needed assessments. The Bayesian approach also can provide bounds not only for the total overstatement and/or understatement error amounts in an accounting population separately, but for the net total error amount as well [5:3].

A great deal of support has been generated to integrate prior subjective knowledge of accounting populations into statistical calculations from statisticians as well as auditors.

> Thus perhaps the strongest argument favoring the formal Bayesian decision process is that this intuition [prior subjective knowledge] is incorporated formally into the decision process. Moreover, by quantifying the intuition in the model, the Bayesian approach tends to prevent haphazard use of this experience [1:111].

> My own view on the problem of estimating the money value of error is that a Bayesian approach is the only satisfactory one from a statistical viewpoint. The auditor's judgement on many issues is highly subjective and thus there is no reason why subjective ideas should not be introduced into the interpretation of his test results [12:279].

Cox and Snell (1979) proposed the use of "infinite population theory as a theoretical foundation for the development of a Bayesian upper bound for the total overstatement amount in the population" (5:499). A 1984 study done by Godfrey and Neter produced the following conclusions concerning the Cox and Snell bounds: (1) the bounds are substantially affected by prior parameter assessments, (2) they are much tighter than the Stringer bound and have high coverage when the actual population contains low error rates, and (3) they are moderately tighter than the Stringer bound for populations whose error amount is large (5:520).

Godfrey and Andrews, in 1982, presented an alternative to classical and other Bayesian procedures. Their method, the finite Bayesian procedure, correctly assumes a finite population (which other Bayesian methods do not) and allows the integration of the auditor's prior information through a prior distribution. They found that their finite Bayesian model more closely approaches the actual population than other procedures and usually requires smaller sample sizes. As with other Bayesian models, the difficulty in the finite Bayesian procedure lies in determining a reasonably accurate prior assessment (4:304-315).

Several other Bayesian approaches have been proposed by statisticians and auditors. McCray, in 1982, assumed a discrete prior distribution for the total error amount and a multinomial distribution for the monetary unit taints. Garstka proposed a compound Poisson model which uses a discrete prior distribution for the mean error taint which is used to calculate an upper error bound for the total error amount. Vanacek's approach uses a beta prior distribution for the population error rate, then obtains Bayesian posterior bounds for the population error rate (5:499).

In 1984, Dworin and Grimlund published a paper proposing a new method of statistical analysis for dollar-unit sampling. Their method was designed to overcome the conservative nature of previously applied upper error bounds. Their new bound, called the moment bound, holds considerable promise for inventory accounts. Results from their study indicate that, when the material limit of the population is less than four percent of book value, the moment bound will lead to the acceptance of more accounts than the multinomial bound. For populations where both understatement and overstatement errors are present, the moment bound provided significantly tighter bounds (2:219,236).

In 1985, Phillips examined modified and unmodified Stringer and Cox and Snell bounds for robustness using 96 accounting populations. He found that none of the modified Cox and Snell bounds were robust and that both the modified and unmodified Stringer bounds were robust at the 95 and 85 percent levels of confidence. The modified Stringer bound produced upper error limits which were approximately 19 percent tighter relative to the unmodified Stringer bound [11:105,106]. Phillips also found that decreasing, uniform, and increasing clustering of errors among line items did not have a significant impact upon bound performance.

In a study done by Helton in 1985, modified and unmodified DUS-cell and Stringer bounds were examined for robustness at varied confidence levels. For the populations under study, he found that the only robust bounds were the unmodified Stringer bounds. However, all coverage failures occurred when a 50 percent line item error rate was introduced into the study population. Also, under certain error conditions, the unmodified Stringer and DUS-cell bounds produced tighter bounds relative to the respective modified bounds [6:4-1].

Characteristics of Accounting Populations. Auditors require knowledge of the frequency, magnitude, distribution, and the possible causes of errors in accounting populations to effectively and efficiently provide statements about the accuracy of the account (7:271). Prior to a study done by Johnson, Leitcn, and Neter in 1981, little had been published about accounting population characteristics. Their study concentrated on accounts receivable and inventory audits and analyzed the magnitude of error rates, the susceptibility of individual items to error within the account, and the degree of overstatement and understatement errors (7:273,274). Highlights from the summary of their results are:

1. There is great variability in the error rates for both types of audits, with the inventory audits

tending to be substantially higher than those for accounts receivable.
2. There is some evidence from the 81 audits which suggests that the error rates in both types of audits may be higher for the larger accounts and for accounts with larger line items than for other accounts.
3. Most errors in receivables audits are overstatement errors, while inventory audits overstatement and understatement are more balanced in number.
4. The distribution of taintings are variable for both types of audits, especially those for inventory audits, and depart substantially from a normal distribution. Quite a few of the tainting distributions for inventories are negatively skewed [7:291].

These results verify that great care must be taken to choose the appropriate methods for sampling, estimating population means, and calculating upper error limits. Assuming a normal distribution is not appropriate for accounting populations. Results from the study indicate that dollar-unit sampling is the most beneficial method, in terms of gathering accurate information, of sampling accounting populations.

Conclusion. Auditors are faced with significant problems in choosing appropriate sampling techniques and upper error limits. Much research has been done trying to deal with these problems, but no clear solution currently exists. Further research in examining current methods and the development of new methods is needed. More efficient and effective auditing procedures will assist auditors in making more accurate and reliable decisions.

SPECIFIC PROBLEM

Auditors must deal with two basic problems with accounting populations. First, accounting populations have relatively few errors. Sampling the populations may result in finding very few errors, which poses significant dilemmas when dealing with classical statistical estimators such as the mean-per-unit, ratio, or difference estimators. Using the sample results to construct confidence intervals for the population error may be unacceptable. The actual confidence intervals provided by classical estimators may be far less than their corresponding nominal levels. This leaves the auditor with no statistical foundation upon which to base his audit opinion. The second major problem facing auditors is determining an acceptable method of quantifying the judgment an auditor wants to make about an account. Classical statistics provide no way for auditors to explicitly incorporate subjective opinions into the final judgment. Bayesian statistical models provide a method by which auditors may introduce their professional judgments of particular accounting populations formally into upper error limit calculations and also help deal with the dilemma of low error rates. Proposed modifications to Cox and Snell Bayesian models have yet to be fully tested and formally reported.

Purpose of the Research

Research Objective 1. The first objective of this research study is to examine robustness at the 90% confidence level for selected modified Cox and Snell upper error limit bounds using study populations with known mean book values, error rates, and error magnitude distributions. For the particular model to be robust, it should, with repetitive sampling, be correct at $(1 - \alpha) \times 100$ percent of the time for each study population.

Research Objective 2. The second research objective is to examine the bound performance using measurements of coverage and rel tightness. Coverage is the proportion of the time, using repetitive sampling, an upper error limit equals or exceeds the true error in each study population. Rel tightness is a ratio of one conservative bound to another less conservative bound. For the purpose of this research, all modified Cox and Snell bounds will be compared to the unmodified Cox and Snell bounds (the conservative bound). If a bound can be found that has adequate coverage while providing tighter (greater rel tightness) upper error limits than the Stringer bound, then that bound would provide auditors a better tool with which to audit accounting populations.

Research Objective 3. The third objective is to examine the performance of the selected bounds by lowering the nominal confidence level to 85%. By lowering the confidence level, it may be possible to achieve coverages equal to higher confidence levels but resulting in tighter bounds.

Research Objective 4. The fourth research objective is to incrementally loosen each of the calculated bounds by 5%, 10%, and 20% and then examine the resulting bounds for robustness, coverage, and rel tightness. By increasing the bounds in this manner, it may be possible to create a robust bound.

Research Objective 5. The fifth research objective is to examine the performance characteristic of power in the selected bounds to be tested. The power of a model is the percent of the time, in repetitive sampling, a bound correctly predicts that there is no material error in a given study population. The probability that the point estimate from an upper error limit model equaling the true error in an accounting population is small. An auditor controls the risk (Type I error) that the model does not predict a material error in the population when there actually is a material error by the chosen. In this study, the performance characteristics of robustness and coverage test the possibility of a Type I error. Also important to the auditor and what this research objective will measure is how well a particular bound avoids a Type II error, predicting a material error in the population when the actual error is not material.

II. METHODOLOGY

Introduction

This chapter presents the sampling approach, upper error limit models, the accounting and study populations, and the performance measurement procedures for the models. To remain consistent with previous research, notation in this research will be similar to that used by Phillips (1985). Much of the work in this research uses the Stringer and modified Stringer bounds for comparison purposes. The Stringer bound is used in practice, and past research has shown it to be extremely conservative. The main computer program, modified for use in this research, is provided in Appendix A.

The Sampling Approach

Johnson, Leitch, and Neter (1981) showed that dollar-unit sampling is the most appropriate sampling method to use for accounting populations [7:291]. Dollar-unit sampling, by providing higher book value line items higher probability of being selected in an audit sample, gets more information out of accounting populations than classical sampling methods. Therefore, dollar-unit sampling will be used for this research. In dollar-unit sampling, the sampling unit is the individual dollar. The following steps outline the procedure for implementing a dollar-unit sample. First, the book value of each line item in the accounting population must be placed into a cumulative list and summed to provide the total reported book value (T). A random sample of the proper size is then selected from the dollars one to T. Each number in the sample refers to a line item in the population. The entire line item to which the sampled dollar belongs is then audited. Lastly, the total error found in an audit unit is prorated proportionately to each dollar in the line item. For this research, a fortran computer program will be modified and used to draw 500 replications of systematic random sample size 200 dollar-units from each of the study populations.

Upper Error Limit Bounds

The upper error limit bound is a dollar figure in which an auditor would be confident at the nominal level that the total dollar error in a population would not exceed. Both Bayesian and non-Bayesian upper error methods in their modified form were included in this study. The non-Bayesian method was the modified Stringer bound which was the basis by which the modified Cox and Snell bounds, the Bayesian methods, were compared. The modified upper error methods involve adding dollar errors identified in the dollar-unit samples to the product of the bound's upper error limit and the number of unsampled dollars remaining in the study population. This method eliminates extrapolating probabalistic error limits to the errors in the sampled units and results in less conservative (tighter) upper error limits.

The Stringer Bound. The Stringer method was introduced by Kenneth W. Stringer in 1963 and uses a Poisson approximation to the binomial distribution. The Stringer upper error limit can be broken down into three components: basic precision, most likely error, and precision gap widening. The basic precision (BP) establishes a minimum upper error limit which an auditor would estimate if no errors were found in the sample. Each error found in a sample raises the upper error limit from this minimum using the most likely error and precision gap widening. The most likely error (MLE) is the auditors best estimate of the probable error in the population based on projecting the dollar-unit sample error onto the population [8:1]. Precision Gap Widening (PGW) represents the amount the total precision gap has widened as a result of finding errors in the sample. The sum of each of the components (BP+MLE+PGW) is known as the upper error limit (UEL) factor. Figure 2.1 provides an example of a Stringer upper error limit resulting from finding four errors of 100%, 80%, 40%, and 20% taintings in a sample of 200 dollar-units of a $1,000,000 population evaluated at the 90% confidence level. For conservatism, it is important to list the errors in descending order by error tainting. This method gives larger value in esimating the upper error limits to the higher taints.

	Factor	x Tainting	x Average Sampling Interval	Dollar Conclusion
Basic Precision	2.31	100%	$5,000	$11,550
Most Likely Error				
1st error	1.00	100	5,000	5,000
2nd error	1.00	80	5,000	4,000
3rd error	1.00	40	5,000	2,000
4th error	1.00	20	5,000	1,000
Precision Gap Widening				
1st error	0.58	100	5,000	2,900
2nd error	0.44	80	5,000	1,760
3rd error	0.36	40	5,000	720
4th error	0.31	20	5,000	310
Total Upper Error Limit				$29,0

Figure 2.1 Example of the Stringer Method at the 90% Confidence Level.

Smith (1979) suggested modifying the Stringer method in order to provide a tighter bound. The modification consisted of applying the calculated upper error limit factor to the unsampled line items in the population and then adding the actual dollar error found in the sample to this result. The modified Stringer bound can be expressed as:

$$MSTR = (T_{yus}/n)(\text{UEL Factor}) + \Sigma e_i \quad (1)$$

where

T_{yus} = the total book value of unsampled line items

n = the sample size

UEL Factor = the same UEL Factor as found in the unmodified Stringer method

e_i = the dollar value of the error in the ith sample line item in error.

For illustration purposes, if the example in figure 2.1 were such that the total book value of the sampled line items is $100,000 and the book value of the line item with the 100% taint is $1,000, the 80% taint is 1,440, the 40% taint is $840, the 20% taint is $480, and the sample size is 200 dollar-units, the modified Stringer method could be calculated as follows:

MSTR = ($900,000/200)(5.848) + $1,460 = $27,776

As can be seen, the modification to the Stringer bound reduces the upper error limit by $1,464, thereby tightening the bound in this particular example by 5%.

<u>The Cox and Snell Bound</u>. Cox and Snell (1979) used infinite population theory to develop a Bayesian upper error method. The Cox and Snell bounds are differentiated by the prior parameter selections or settings of the dollar-unit error rate (π), the mean taint (μ_t), and the prior probability distribution of π (designated as σ_π) and μ_t (designated as σ_μ). The following calculation is performed in developing an unmodified Cox and Snell upper error limit:

$$UEL_{cs} = [[m\bar{t}+(b-1)\,\mu_0]/[a/\pi_0+n]][(m+a)/(m+b)]\;F[(1-\alpha);2(m+a),2(m+b)] \quad (2)$$

and

$$CS = (UEL_{cs})(T_y) \quad (3)$$

where

π_0 = the expected value of the error rate

$a = \pi_0^2/\sigma_\pi^2$ where σ_π^2 is the expected value of the variance of the population error rate

$_0$ = the given expected value of the mean taint

$b = (\mu_0^2/\sigma_\mu^2) + 2$ where σ_μ^2 is the expected value of the variance of the population mean taint

n = the dollar-unit sample size

m = observed number of sample dollar-units in error

$\bar{t}$ = the sample mean taint or simply the sum of the sample taints divided by m

$F[(1-\alpha);2(m+a),2(m+b)]$ = the F distribution value at the nominal confidence level of $(1-\alpha)$ with $2(m+a)$ and $2(m+b)$ degrees of freedom in the numerator and denominator respectively

T_y = total population book value

For example, if a sample of 200 dollar-units has four errors with taints of .2, .4, .8, and 1.0 in a $1,000,000 population, the resulting Cox and Snell upper error bound from prior parameter settings of π_0 equals .20, σ_π equals .20, μ_0 equals .40, and σ_μ equals .20, will be $31,386 at the 90% nominal confidence level. If another error were found in a sample of the same population with the same taints as the previous example (meaning a taint of .6) and using the same prior parameter settings, the resulting 90% confidence level bound will be $35,143. Thus, finding an additional error increases the bound by $3,757. If, in the first example, a different Cox and Snell bound were chosen which had prior parameter settings of π_0 equals .20, σ_π equals .20, μ_0 equals .40, and σ_μ equals .20, the resulting upper error limit bound at the 90% confidence level would be $22,280.

The modified Cox and Snell bound is calculated in the same manner as the modified Stringer bound. It is obtained by statistically projecting the upper error limit to the total dollar value of the unsampled line items (T_{yus}) then adding the total dollar value of the actual errors found in the sample (Σe_i). The modified Cox and Snell bound can be written as:

$$MCS = (UEL_{cs})(T_{yus}) + \Sigma e_i \qquad (4)$$

If, in the first example given for the unmodified Cox and Snell bound, a modified Cox and Snell bound is calculated and the total dollar value of the sampled line items is $100,000, then the resulting 90% confidence level bound will be $29.447. The modification therefore reduced the upper error limit by $1,939 or tightened the bound by 6.2 percent.

Prior Probability Parameter Settings

As previously explained, each Cox and Snell bound is distinguishable by the particular prior probability values for the dollar-unit error rate (π), the mean taint (μ_t), and the standard deviations of both parameters (σ_π and σ_μ). The particular bounds to be examined in this study were selected based upon the results of the Phillips (1985) research in which no modified Cox and Snell bounds were found to be robust. Five modified Cox and Snell bounds, each somewhat looser than the bounds in the Phillips (1985) research, were examined.

Prior expected values for the dollar-unit error rate (π_0) included in this research were four bounds at .20 and one at .05 with each having the same standard deviation (σ_π) of .20. Prior expected values for the mean taint (μ_0) ranged from small, .05, to medium, .10 and .20, to large, .40. The associated standard deviations (σ_μ) were selected to give variability and ranged from .10 to .20. Table 2.1 provides the specific prior expectation parameters for each of the modified Cox and Snell bounds examined in this research. Note that the different bounds are distinguished by A through E. This convention of identification will be maintained throughout this research and in every case refers to the particular probability parameter settings in Table 2.1. In order to accomplish the incremental modifications as specified in research objective 4, for every modified Cox and Snell bound calculated, three more bounds were calculated. The modified Cox and Snell bounds were multiplied by 1.05, 1.10, and 1.20 to provide 5, 10, and 20 percent loosening.

Table 2.1

Prior Probability Parameter Settings
of Selected Cox and Snell Bounds

Bound	π_0	σ_π	μ_0	σ_μ	a	b
AMCS	.05	.20	.40	.10	.06	18.00
BMCS	.20	.20	.05	.20	1.00	2.06
CMCS	.20	.20	.10	.15	1.00	2.44
DMCS	.20	.20	.20	.20	1.00	3.00
EMCS	.20	.20	.40	.20	1.00	6.00

The Accounting Population

The main accounting population used for this research was acquired from the University of Michigan through Dr. James Godfrey. It consists of 8069 inventory accounts of a major pharmaceutical manufacturer. Account balances of $100,000 and greater have been deleted on the presumption that they would be audited on a 100% basis in actual practice. Specific characteristics of the accounting population are listed in Table 2.2.

Table 2.2

Descriptive Statistics of
Accounting Population Book Values

Number of Accounts	8069
Mean	$1,191.39
Standard Deviation	$3,739.53
Minimum	$0.01
Maximum	$99,328.32
Total	$9,613,301.00
Variance	14,360,566.76
Skewness	11.4292
Kurtosis	189.927
Coefficient of Variation	3.18

The Study Populations

In order to maintain a high degree of external validity, the study populations were created with extreme care. As noted previously in the background, Johnson, Leitch, and Neter (1981) found while inventory populations contain both overstatement and understatement errors, the majority of inventory populations still contained significant numbers of overstatement errors. Only overstatement errors were included in the population because the accounting population for this study is an inventory account and Cox and Snell bounds are not designed to deal with understatement errors.

A broad range of mean error rates (π_0)were selected for this study to provide a rigorous test for the models examined. The six mean error rates are .80 (high), .25 and .10 (medium), and .5, .01, and .005 (low). If a model proves robust (ie, correct approximately (1-α) x 100 percent of the time) for this range (favorable to unfavorable) of mean error rates, auditors need not be concerned about accurately predicting prior parameters for the accounting population they are auditing. They can be confident at the nominal level that no matter what error rate is encountered in the audited population, the actual error will not exceed the predicted upper error limit provided by the model.

Prior to seeding the population with errors, the population was sorted from low book values to high book values. The population was then divided into two strata such that the total book values in each statum were equal (total low book value = total high book value). The low book value accounts were identified as stratum 1 and the high book value accounts were stratum 2.

Four different combinations of mean taints were introduced into the population by strata as shown in Table 2.3. They were selected to provide significant contrasts among the study populations with a range from very high to very low mean taints.

Table 2.3

Mean Taints

Stratum 1	Stratum 2
.8	.4
.4	.2
.2	.1
.1	.05

Errors were seeded into the population to reflect the findings of Johnson, Leitch, and Neter (1981). First, 10% of all errors in stratum 1 were randomly assigned 100% taints. Second, the other 90% of the errors in stratum 1 and all of the errors in stratum 2 were generated using an exponential distribution with the mean values shown in Table 2.2. In order to make the study populations more realistic, the exponential taint distributions were truncated at 1.0 in accordance with Godfrey and Neter (1984). Thus, (6 mean error rates x 4 mean error taints) different study populations were created to examine the performance of the bounds. The particular characteristics of each study population are provided in Appendix B.

Performance Measurement Procedures

Performance of the modified Cox and Snell bounds was based upon robustness, coverage, rel tightness and power with respect to changes in error rate, mean taint, and error amount intensity. A robust bound must, with repetitive sampling, be correct $(1 - \alpha) \times 100$ percent of the time for all study populations. Correctness is defined as a calculated upper error limit equaling or exceeding the actual error in the study population. Coverage is the percent of correct bounds out of 500 replications for each study population. The mean rel tightness measure constitutes the degree to which a calculated modified Cox and Snell bound reduced the projected error in a study population as compared to that indicated by the unmodified Cox and Snell bound. That is, with repetitive sampling in a given population, mean rel tightness is the ratio of the mean unmodified Cox and Snell bound to the mean modified Cox and Snell bound and can be written algebraically as

$$\text{Mean Rel Tightness} = (\Sigma CS_i / MCS_i)/500$$

where

CS_i = the unmodified Cox and Snell bound for replication i,

MCS_i = the modified Cox and Snell bound for replication i, and

i = 1, ..., 500.

For measurement of mean rel tightness for the different nominal confidence level bounds, the conservative bound was the 90 percent nominal confidence level bound and can be written algebraically as

$$\text{Mean Rel Tightness} = (\Sigma MCS90_i / MCS85_i)/500$$

where

MCS90 = the modified Cox and Snell bound at the 90 percent nominal confidence level for replication i

MCS85 = the modified Cox and Snell bound at the 85 percent nominal confidence level for replication i

i = 1, ..., 500.

In the context of an auditing situation, an auditor generally sets a level of error in a population at or above which the auditor will reject the population as being correct. This level of error is known as the level of materiality or simply the material error. When the true population total error amount is less than materiality and the correct decision is to accept the population, a bound which provides adequate coverage may provide bounds which equal or exceed the material amount and cause the auditor to make the incorrect decision of rejecting the population. The probability of rejection performance or power of a particular upper error limit bound is determined by the level of materiality selected as criteria for measurement. In order to measure the selected bounds in this research for power, three levels of materiality were selected: five percent, two and one-half percent, and one-tenth of one percent of the total book value. The low materiality level of one-tenth of one percent was selected for accounting populations in which possibly a single high value item missing might be of significance or material. Therefore, for those study populations which do not contain a material error, probability of rejection performance can be measured as the percent of the time, in repetitive sampling, the bound equals or exceeds the selected level of materiality.

Analysis of Results

The study populations were sorted in ascending order based on the ratio of total dollar error (T_e) to the total population book value (T_y). This ratio is known as the error amount intensity (EAI) and can be expressed algebraically as the line item error rate times the mean taint or

$$EAI = T_{LI} \times T_t \quad (5)$$

where

$$T_{LI} = T_Y(e)/T_Y \quad \text{and}$$

$$T_t = T_e/T_Y(e)$$

T_Y = total book value of all line items

$T_Y(e)$ = total book value of line items containing errors

T_e = total population error amount

The study populations were then divided into four EAI categories, low, medium, high, and very high based on "logical breaks" in the EAI range. Table 2.4 identifies the EAI categories and their ranges while Table 2.5 identifies the specific EAI of each study population and the EAI category in which the study population lies. Each bound will be examined over all study populations for its performance in robustness and by each EAI category for its performance in coverage, mean rel tightness, and power.

TABLE 2.4

ERROR AMOUNT INTENSITY (EAI)* CATEGORIES

Category	EAI Range	Number of Study Populations
Low	.00022 - .00170	6
Medium	.00442 - .04039	12
High	.06342 - .12081	4
Very High	.25091 - .37291	2
Total		

Table 2.5

Study Populations (P) by Error Amount Intensity

Low (6)		Medium (12)		High (4)		Very High	
P	EAI	P	EAI	P	EAI	P	EAI
21	.00022	20	.00442	1	.06342	3	.25091
22	.00067	13	.00457	7	.07626	4	.37291
17	.00083	19	.00562	8	.11360		
23	.00121	9	.00707	2	.12081		
18	.00145	14	.00847				
24	.00170	15	.01364				
		10	.01375				
		16	.02045				
		5	.02177				
		11	.02608				
		12	.03839				
		6	.04039				

* study population total dollar error as a proportion of total book value

III. Results and Analysis

Introduction

This chapter contains the results of the analysis performed on the data generated from the research. The chapter is presented in the order of the research objectives and devotes a major section of the discussion to each. The first area discussed is bound robustness with respect to all the bounds including the unmodified and modified Stringer and Cox and Snell bounds. The discussion then transitions to mean coverage and mean rel tightness performance measures for each error amount intensity (EAI) category for the unmodified and modified Cox and Snell bounds. Analysis of bound performance when the nominal confidence level is lowered from 90 percent to 85 percent will follow with the discussion of power presented last.

Due to the large number of bounds, the reader needs to understand the bound nomenclature. The unmodified Stringer bounds are STR90 and STR85 meaning the unmodified Stringer bounds at the 90 and 85 percent nominal confidence levels, respectively. The last two numbers in the nomenclature refer to the bound's particular nominal confidence level which is either 90 or 85 percent. As stated in the previous chapter, the Cox and Snell bounds are distinguished by their particular prior probability parameter settings. There are five prior parameter settings (A through E) as identified in

Table 2.1. The unmodified, modified, and incrementally modified Cox and Snell bounds' first letter in the nomenclature will refer to these prior parameter settings. For example, ACS90 refers to the unmodified Cox and Snell bound at the 90 percent nominal confidence level with prior parameter settings of π_0 is .05, σ_π is .20, μ_0 is .40, and σ_μ is .10. AMCS90 refers to the modified Cox and Snell bound at the same nominal confidence level and with the same prior parameter settings. AM1M90 refers to the first incremental increase or 5 percent loosening of the modified Cox and Snell bound at the same nominal confidence level and with the same prior parameter settings. The second incremental increase or 10 percent loosening of the bound is AM2M90 and the third incremental increase or 20 percent loosening of the bound is AM3M90.

Measurement of Bound Robustness

The first research objective was to examine the bounds for robustness. A $(1 - \alpha)$ upper error limit bound is robust if the bound is correct, with repetitive sampling from the population, $(1 - \alpha) \times 100$ percent of the time. To meet this criterion in this research, the particular bound must attain actual coverage at the nominal confidence level or higher for all study populations.

The unmodified and modified Stringer bounds at both the 90 and the 85 percent nominal confidence levels were robust for all study populations. Table 3.1 presents the actual mean coverages attained by each of the unmodified and modified Stringer bounds. All are well above the nominal confidence level which provides further evidence of the conservative nature of the Stringer bound. No unmodified or modified Cox and Snell bounds were robust.

Table 3.1

Mean Coverage of the Stringer Bounds

Bound	Mean Coverage
STR90	.998
MSTR90	.990
STR85	.992
MSTR85	.973

Bound Performance in Coverage and Mean Rel Tightness

The second research objective was to examine bound performance in coverage and mean rel tightness and to identify those bounds which provided adequate mean coverage. Coverage is the percent of the time in repetitive sampling the calculated upper error limit equals or exceeds the actual error in each study population. Mean rel tightness of the modified Cox and Snell bounds was measured with respect to the corresponding unmodified Cox and Snell bound. Although there were no robust unmodified or modified Cox and Snell bounds, some bounds performed adequately in mean coverage for particular error amount intensity (EAI) categories. Detailed information on each bounds performance in mean coverage and mean rel tightness by EAI category is provided in Appendix C.

Both unmodified Cox and Snell bounds D and E (DCS90 and ECS90) performed well in the low EAI category. These two bounds had adequate coverage for all six of the study populations in this EAI category both with mean coverages of 100 percent. The modified Cox and Snell bounds D and E (DMCS90 and EMCS90) also performed well in the low EAI category. DMCS90 and EMCS90 adequately covered all six study populations in this EAI category both with mean coverages of 100 percent while providing 18.3 percent and 20.7 percent (mean rel tightness measures of 118.3 percent and 120.7 percent) tighter bounds respectively than the unmodified Cox and Snell bounds. This finding indicates that the unmodified Cox and Snell bound performs in a relatively conservative fashion in populations with relatively low error amount intensities since the modified bounds tightened the unmodified bounds by 18.3 percent for the D bound and 20.7 percent for the E bound while not declining in actual mean coverage performance.

While both modified Cox and Snell bounds D and E (DMCS90 and EMCS90) had good mean coverage (100 percent) in the low EAI category, DMCS90 provided bounds which were 133.1 percent (mean rel tightness measure of 233.1 percent) tighter than EMCS90. The difference in the two bounds is in the mean taint prior probability settings (μ_0). DMCS90 has a μ_0 of .20 while EMCS90 has a μ_0 of .40. This indicates that the bounds are very sensitive to the mean taint prior probability parameter settings when dealing with accounting populations with error amount intensities similar to those of the study populations in the low EAI category. Auditors, knowing they are dealing with populations with low EAI, would likely desire the tighter bound, DMCS90, since it provides actual mean coverages equivalent to EMCS90 but resulting in much tighter bounds.

In trying to determine what characteristics of DMCS90 and EMCS90 which made them perform well in the low EAI category, the prior probability parameter settings for the error rate and the mean taint appear to be significant. Figure 3.1 displays the modified Cox and Snell bound and their respective prior probability parameter settings. Bounds D and E are associated with a combination of high mean taint, error rate and distributions for both $_0$ and $_0$ relative to bounds A, B, and C. While bound A has a high mean taint, its low prior probability error rate setting may have detrimentally impacted its mean coverage performance. None of the unmodified or modified Cox and Snell bounds provided adequate mean coverage in any of the other three EAI categories (medium, high, or very high).

	π_0	.05	.20
	σ_π	.20	.20
μ_0	σ_μ		
.05	.20		Bound B
.10	.15		Bound C
.20	.20		Bound D
.40	.20		Bound E
	.10	Bound A	

Figure 3.2. Prior Parameter Settings of Selected Cox and Snell Bounds

Bound Performance at the 85 Percent Nominal Confidence Level

The third research objective was to examine the performance of the selected Cox and Snell bounds when the nominal confidence level is reduced from 90 percent to 85 percent. As with the bounds at the 90 percent nominal confidence level, only unmodified and modified Cox and Snell bounds D and E provided adequate coverage in the low EAI category and no bounds provided adequate coverage in any of the three other EAI categories. Table 3.2 presents the actual mean coverages at both nominal confidence levels for unmodified and modified Cox and Snell bounds D and E. Unmodified and modified Cox and Snell bound D (DCS85 and DMCS85) provided acceptable mean coverage for five of the six study populations with low EAI. Both bounds had actual mean coverages of 91.2 percent with the modified bound (DMCS85) giving 17.6 percent (mean rel tightness measure of 117.6 percent) tighter bounds than the unmodified bound (DCS85). The study population not adequately covered by DCS85 and DMCS85 was study population number which had the highest EAI of the study populations in the low EAI category. Modified Cox and Snell bound D (DMCS85) at the 85 percent nominal confidence level provided actual mean coverages above 91 percent in the low EAI category and provided 23.4 percent (mean rel tightness measure of 123.4 percent) tighter bounds than the same bound at the 90 percent nominal confidence level.

Unmodified and modified Cox and Snell bound E at the 85 percent nominal level (ECS85 and EMCS85) adequately covered all six study populations in the low EAI category and both bounds had actual mean coverages of 100 percent. EMCS85 provided a 20.5 percent (mean rel tightness measure of 1.205) bound than the unmodified Cox and Snell bound (ECS85) at the same nominal confidence level and EMCS85 also tightened the modified Cox and Snell bound at the 90 percent nominal confidence level (EMCS90) by 20.5 percent.This finding is significant because much tighter (20.5 percent) upper error limits may be predicted at the 85 percent nominal confidence level with the same actual confidence levels as with the 90 percent nominal confidence level.

Table 3.2

Actual Mean Coverages of Cox and Snell Bounds D and E in the Low EAI Category*

Nominal Level	Unmodified Bounds DCS	ECS	Modified Bounds DMCS	EMCS
90%	100	100	100	100
85%	91	100	91	100

* all figures in percent

Although modified Cox and Snell bounds D and E at the 85 percent nominal confidence level performed well above the nominal level in mean coverage, bound D provided much tignter bounds than bound E. In the low EAI category, D bounds were 138.8 percent (mean rel tightness measure of 238.8 percent) tighter than the E bounds. This difference in tightness accounts for the decrease in mean tightness by the D bound. Therefore, if an auditor is dealing with populations known to have low EAI and he or she is willing to accept slightly more risk, then the modified Cox and Snell bound D at the 85 percent nominal confidence level (DMCS85) would be useful.

Bound Performance with the Incremental Modifications

The fourth research objective was to incrementally increase the modified Cox and Snell bounds by 5, 10, and 20 percent in order to possibly improve bound performance.

Since modified Cox and Snell bounds D and E performed well in the low EAI category, the incrementally modified bounds D and E also performed well in coverage. However, even with the third incremental modification (20 percent loosening of the modified Cox and Snell bound) there was no improvement in mean coverage in the low EAI category. The mean rel tightness measure deteriorated steadily for each incremental modification. This was the case for both 90 percent and 85 percent levels of confidence. Therefore, since the incremental modifications in the low EAI category provided no improvement in coverage and was detrimental to mean rel tightness, the incremental modifications to the modified Cox and Snell bounds were not successful in improving the modified Cox and Snell bounds in the low EAI category.

The incremental modifications in the medium and high EAI categories provided no improvement over the modified Cox and Snell bounds. In the very high EAI category, the third incremental modification to modified Cox and Snell bound A (AM3M90 and AM3M85) at both the 90 percent and the 85 percent nominal confidence level provided good mean coverage. These bounds covered both of the two study populations in the very high EAI category at the nominal levels or higher with a mean coverage well above the nominal levels at 94.6 percent and 88.6 percent respectively. These bounds, by loosening the modified Cox and Snell bound by 20 percent, resulted in a mean rel tightness measure looser than the unmodified Cox and Snell bound with the same prior parameter settings. The 90 percent nominal confidence level bound (AM3M90) provided a mean rel tightness measure of 85.6 percent or 14.6 percent looser than the unmodified Cox and Snell bound. The 85 percent nominal confidence level bound (AM3M85) provided a mean rel tightness measure of 85.3 percent or 14.7 percent looser than the unmodified Cox and Snell bound at the same nominal confidence level. AM3M85 provided bounds which were 2.1 percent (mean rel tightness measure of 102.1 percent) tighter than the 90 percent nominal confidence level bound (AM3M90). Of the five bounds studied, bound A has the highest b value ($\lfloor \mu_0^2/\sigma_\mu^2 \rfloor + 2$) of 18.00 which, combined with the highest incremental modification, may have been the two factors which loosened the bound sufficiently to provide adequate mean coverage.

Measurement of Bound Power

The fifth research objective was to measure the probability of a bound rejecting the population when in actuality there was not a material error in the study population. The lowest level of materiality (.1 percent of total book value) was used to test modified Cox and Snell bounds D and E in the low EAI category. At this level of materiality, three study populations (17, 21, and 22) have actual errors intensities less than the material error. Modified Cox and Snell bounds D and E at both the 90 percent and 85 percent nominal confidence levels incorrectly rejected the study populations 100 percent of the time. Further investigation into the cause for the bounds' high rejection rate revealed that the possibility of a lower limit to the bounds may exist. None of the unmodified or modified Cox and Snell bounds studied in this research could provide an upper error limit anywhere near the .1 percent of the total book value level of materiality; all the bounds were well above this level of materiality. This result indicates that the Cox and Snell bounds in this research may be too conservative for populations with low error amount intensities and where low levels of materiality are important.

IV. Summary, Conclusions, and Recommendations For Future Research

Summary

The results of this study extend research to find Bayesian approaches for auditing accounting populations. Five Cox and Snell bounds at both the 90 percent and the 85 percent nominal confidence levels and modifications to include known sample errors in bound calculations were examined. Incremental loosening of 5, 10, and 20 percent of each bound was accomplished to seek bound improvements. The power of each Cox and Snell bound found to provide adequate coverage was also tested. Performance of the unmodified and modified Stringer bounds was also tested using the same study populations.

The unmodified and modified Stringer bounds were robust at both confidence levels. Two of the unmodified and modified Cox and Snell bounds, D and E, at both confidence levels had adequate actual mean coverages in the low error amount intensity (EAI) study populations. In the low EAI category, modified Cox and Snell bound D at the 90 percent nominal confidence level provided 18.3 percent while bound E provided 20.7 percent tighter bounds than their correspon-ding unmodified bounds. Although bounds D and E had similar actual mean coverages, modified Cox and Snell bound D, with a mean taint (μ_0) of .20, provided bounds which were 133 percent tighter than bound E, with a μ_0 of .40.

At the 85 percent nominal confidence level, actual mean coverages of unmodified and modified Cox and Snell bound D exceeded 90 percent and reached 100 percent with bound E in the low EAI category. However, significant increases in bound tightness were noted for both bounds as the nominal level was decreased from 90 to 85 percent. Modified Cox and Snell bound D had 17.6 percent tighter bounds and modified bound E had 20.5 percent tighter bounds at the lower nominal confidence level. Although the mean coverages of modified Cox and Snell bound D at the 85 percent nominal level were lower than bound E, the increase in mean rel tightness of bound D was significant with 138.8 percent tighter bounds than bound E.

The only bound to provide adequate mean coverage in another EAI category was the third (20 percent) incremental loosening of modified Cox and Snell bound A at both the 90 and 85 percent nominal confidence levels in the high EAI category. This degree of loosening the modified Cox and Snell bound resulted in bounds which were more than 14 percent looser than the unmodified Cox and Snell bound.

With respect to power, no bounds were acceptable at the .1 percent of total book value level of materiality. Even Modified Cox and Snell bound D with its increases in mean rel tightness failed the power test providing 100 percent rejection of populations without a material error. This finding indicates that even the Cox and Snell bounds examined in this research may be too conservative in low EAI populations.

Conclusions

Even though the sensitivity of Cox and Snell bounds to their prior probability settings makes prediction of bound behavior difficult, this research has shown that modified Cox and Snell bounds D and E may provide auditors with a better tool with which to audit accounting populations with low error amount intensities than the Stringer bound. In the low EAI these two bounds, D and E, had good mean coverages while providing significant increases in rel tightness.

Recommendations for Future Research

In this research, mean rel tightness was measured with respect to a more conservative bound. Further research might be done using the actual error in the study population as a basis. Although this method of calculating rel tightness would only be applicable in the laboratory situation where actual errors are known, it may provide a broader basis to compare bounds. Not only could one bound be compared to another for tightness, but the extent of the bound's conservatism is measured directly.

Auditors should consider the implementation of modified Cox and Snell bound D and E in accounting populations with low error amount intensities.

Further research should be done with other modified Cox and Snell bounds to determine those that may provide auditors with better upper error limit bounds.

Appendix A: Fortran Computer Program

```
*****************************************************************
C
C     Author:  Lt Col J.J. Phillips
C
C     Revised:  Capt Blaine F. Webber
C
C****************************************************************
C****************************************************************
C
C    MAIN PROGRAM
C
C****************************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300)
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP,TETYY
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,TYE
      COMMON RANARY(9000),DSEED,TOT,ME,LE,CNTIT,CNTEM
      OPEN(1,FILE='sampl.out )
      CALL FSEEK(1,0,2)
      OPEN(4,FILE='bound.dat')
      CALL FSEEK(4,0,2)
      OPEN(9,FILE='info.out')
      CALL FSEEK(9,0,2)
      REWIND 1
      REWIND 4
      REWIND 9
      WRITE(9,100)
 100  FORMAT(//10X,'BEGIN SIMULATION.............')
      CALL INITA
      CALL ERRATE
      STOP
      END
C****************************************************************
C
      Subroutine Errate
C
C****************************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
```

```
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300)
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP,TETYY
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
      COMMON RANARY(9000),DSEED,TOT,ME,LE,CNTEM
      INTEGER CNTIT,CNTEM
      REAL LERA(6),MID,X(1)
      DOUBLE PRECISION DSEED
      NR=0
      I=0
      CNTIT=0
      ISDYPP=0
      CNTEM=0
      M=0
      L=0
      KK=0
      IZZ=0
      DSEED=123457.D0
C These are the study population line item error rates.
      LERA(1)= 0.8
      LERA(2)= 0.25
      LERA(3)= 0.10
      LERA(4)= 0.05
      LERA(5)= 0.01
      LERA(6)= 0.005
C These are the study population error taints.
      TL(1)=.10
      TL(2)=.2083
      TL(3)=.8131
      TL(4)=10.0
      TH(1)=.0505
      TH(2)=.10
      TH(3)=.2083
      TH(4)=.8131
C Read the actual accounting population values into arrays.
      Open(unit=8, file='file3',status='old')
      REWIND 8
      TOTARY(1)=0.0
      DO 55 i=1,8069
   50 Read(8,*)BV,TOT,IND
      BVARY(I)=BV
      ERRARY(I)=0.0
      TOTARY(I)=totary(I-1)+bvary(i)
      AVARY(I)=0.0
      TNTARY(I)=0.0
      INDEX(I)=I
   55 CONTINUE
      CLOSE(8)
      I = I-1
```

```
C Calculate the midpoint value of the accounting population.
      MID=Totary(I)/2
      K=1
C Calculate the number in the low book value stratum (CNTIT)
C and the number in the high book value stratum (CNTEM).
   57 If(MID.GE.Totary(K))then
         CNTIT=CNTIT+1
         K=K+1
         GO TO 57
      Else
         CNTEM=I-CNTIT
      END IF
C Create the  study population by combining 6 error rates
C and 4 error taints.
       Do 2000 LE=1,6
C Call the subroutine to identify the line items with error.
      Call Errlin
C Identify 10 percent of the low book value items to receive
C 100 percent taints.
      IZZ = 0
      DO 500 KM = 1, CNTIT
         IF (RANARY(KM).EQ.0) then
            GO TO 500
         ELSE
            IZZ = IZZ+1
         END IF
 500  Continue
      IZZ = Int(IZZ*0.1)
c  This do loop calculates study populations  by  combining
c  each error rate with 4 mean error taints.
        DO 1000 ME=1,4
        KNT=0
           DO 650 KK=1,I
              If(Ranary(KK).NE.0)then
                If(KK.LE.CNTIT)then
                   If(KNT.LE.IZZ)then
                     AVARY(KK)=2*BVARY(KK)
                     KNT=KNT+1
                   Else
  550                Call GGUBS(DSEED,1,X)
                         EEXP=-TL(ME)*ALOG(X(1))
                     If(EEXP.GE.1.0)Go to 550
                     AVARY(KK)=BVARY(KK)*(1+EEXP)
                   End if
                Go to 630
                Else
  560              Call GGUBS(DSEED,1,X)
                   EEXP=-TH(ME)*ALOG(X(1))
                   If(EEXP.GE.1.0)Go to 560
                   AVARY(KK)=BVARY(KK)*(1+EEXP)
                End if
                Go to 630
```

```
              Else
                AVARY(KK)=BVARY(KK)
              End if
 630          ERRARY(KK)=AVARY(KK)-BVARY(KK)
              TNTARY(KK)=ERRARY(KK)/BVARY(KK)
 650        Continue
            ISDYPP=ISDYPP+1
            Call Info
            CALL STRPOF
            Print*,'Processing sample ... '
            ERK=TH(ME)
            CALL SAMPL
            Do 900 KL=1,I
              Avary(KL)=0.0
              Errary(KL)=0.0
              Tntary(KL)=0.0
 900        Continue
1000     Continue
2000   Continue
       Close(4)
       END
C*************************************************************
       Subroutine Errlin
C*************************************************************
       COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
       COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
       COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
       COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
       COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
       COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
       COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
       COMMON AAVARY(300),EERARY(300),TTNTRY(300)
       COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
       COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP,TETYY
       COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
       COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
       COMMON RANARY(9000),DSEED,TOT,ME,LE,CNTEM
       INTEGER IX(9000),G,NSAMP,NPOP,IP,MPOP,MSAMP,IER
       INTEGER CNTIT,CNTEM
       REAL LERA(6),POP(1),SAMP(1),MID
       DOUBLE PRECISION DSEED
       J=0
       K=0
       KM=0
       G=0
       NSAMP=0
       IP=0
       NPOP=I
       MPOP=NPOP
       DO 5 KL=1,I
          IX(KL)=0
 5     CONTINUE
```

```
      Do 10 J=1,I
         Ranary(J)=0.0
   10 Continue
C Calculate the number of line items to be in
C error(LERA(M)).
      NSAMP=I*LERA(LE)
C Call a random number generator which gives you NSAMP
C number of random numbers in array IX.
C Transfer the line items to be in error into array RANARY
   20 Call GGSRS(DSEED,0,NPOP,IP,MPOP,POP,NSAMP,MSAMP,
     * SAMP,IX,IER)
      Do 30 IG=1,NSAMP
         K=IX(IG)
         RANARY(K)=K
   30 Continue
      Return
      End
C*************************************************************
C
      SUBROUTINE SAMPL
C
C*************************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300)
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
      COMMON RANARY(9000),DSEED,TOT,ME,LE,TETYY,CNTEM
      REAL MCS90(5),MMC190(5),MMC290(5),MMC390(5),MCS85(5)
      REAL MMC185(5),MMC285(5),MMC385(5)
      IGY=0
      J=0
      DO 100 JZZ=1,500
         SAMPBV=BIGBV
         SAMPER=BIGER
         XMLE=0.0
         PGW90=0.0
         PGW85=0.0
         X=0.0
         IM=0
         TOTANT=0.0
         ITOOT=0
         DO 10 ITO=1,200
            A(ITO)=0.00
 10      CONTINUE
```

```
      TZ=TOT
      CALL STEP1
      TOT=TZ
      IGY=0
      DO 20 IK=1,N
         SAMPER=SAMPER+EERARY(IK)
         SAMPBV=SAMPBV+BBVARY(IK)
         IF (TTNTRY(IK).NE.0.0) THEN
             ITOOT=ITOOT+1
             A(ITOOT)=TTNTRY(IK)
         ELSE
             GO TO 20
         END IF
20    CONTINUE
      IF (ITOOT.LE.1) GO TO 50
      CALL SORTA(A,200, ITOOT)
50    CONTINUE
      CALL BOUND1
      CALL BOUND2
      WRITE(4,60) ISDYPP,JZZ,N,TE,LERA(LE),TH(ME)
      WRITE(4,70) IM,TOT,SAMPBV,SAMPER,SIMPER
60    FORMAT(1X,3(I4,2X),3(F12.2,2X))
70    FORMAT(1X,I5,2X,4(F12.2,2X))
      WRITE(4,80)STR90,MSTR90,STR85,MSTR85
      WRITE(4,80)CS90(1),CS90(2),CS90(3),CS90(4),CS90(5)
      WRITE(4,80)MCS90(1),MCS90(2),MCS90(3),MCS90(4),
     *           MCS90(5)
      WRITE(4,80)MMC190(1),MMC190(2),MMC190(3),
     *           MMC190(4),MMC190(5)
      WRITE(4,80)MMC290(1),MMC290(2),MMC290(3),
     *           MMC290(4),MMC290(5)
      WRITE(4,80)MMC390(1),MMC390(2),MMC390(3),
     *           MMC390(4),MMC390(5)
      WRITE(4,80)CS85(1),CS85(2),CS85(3),CS85(4),CS85(5)
      WRITE(4,80)MCS85(1),MCS85(2),MCS85(3),MCS85(4),
     *           MCS85(5)
      WRITE(4,80)MMC185(1),MMC185(2),MMC185(3),
     *           MMC185(4),MMC185(5)
      WRITE(4,80)MMC285(1),MMC285(2),MMC285(3),
     *           MMC285(4),MMC285(5)
      WRITE(4,80)MMC385(1),MMC385(2),MMC385(3),
     *           MMC385(4),MMC385(5)
80    FORMAT(1X,5(F14.2,2X))
100   CONTINUE
      RETURN
      END
C*************************************************************
C
      SUBROUTINE STEP1
C
C*************************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
```

```
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300)
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
      COMMON RANARY(9000),DSEED,TOT,ME,LE,TETYY,CNTEM
C
      REAL X(1)
      DOUBLE PRECISION DSEED
 14   CALL GGUBS(DSEED,1,X)
      IF (X(1).EQ.0.0) GO TO 14
      Y=X(1)*SKIP
      DO 20 IMY=1,N
         TIJ=Y+(SKIP*(FLOAT(IMY)-1.0))
         CALL SEARCH(TIJ,LINEI)
         IGY=IGY+1
         BBVARY(IGY)=BVARY(LINEI)
         AAVARY(IGY)=AVARY(LINEI)
         EERARY(IGY)=ERRARY(LINEI)
         TTNTRY(IGY)=TNTARY(LINEI)
         TTOTRY(IGY)=TOTARY(LINEI)
         IINDEX(IGY)=INDEX(LINEI)
 20    CONTINUE
C     WRITE(1,50)JZZ,IGY
C50   FORMAT(10X,'ITERATION= ',I5,'  SAMPLE SIZE= ',I5)
C     DO 60 IGH=1,IGY
C        WRITE(1,80)BBVARY(IGH),AAVARY(IGH),EERARY(IGH),
C    *   TTNTRY(IGH),TTOTRY(IGH),IINDEX(IGH)
C80      FORMAT(5X,5F12.3,I5)
C60   CONTINUE
      RETURN
      END
C*************************************************************
C
      SUBROUTINE SEARCH(TIJ,LINEI)
C
C*************************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300)
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
```

```
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
      COMMON RANARY(9000),DSEED,TOT,ME,LE,TETYY,CNTEM
      INTEGER MAXPT,MINPT,MIDPT
      MINPT=1
      MAXPT=I
 10   MIDPT=(MAXPT-MINPT)/2+MINPT
      IF ((MAXPT-MINPT).EQ.1) THEN
         LINEI=MAXPT
         RETURN
      ELSE
         IF (TIJ.LE.TOTARY(MIDPT)) THEN
             MAXPT=MIDPT
         ELSE
             MINPT=MIDPT
         END IF
      END IF
      GO TO 10
      END
C*************************************************************
C
      SUBROUTINE SORTA(A,ND,NS)
C
C*************************************************************
      REAL A(ND),TEMP
      INTEGER I,LASTS,LASTI,SSTART
      LOGICAL INSORT
      SSTART=NS-1
      LASTS=1
      LASTI=LASTS
      INSORT=.FALSE.
 10   CONTINUE
      IF (.NOT.INSORT) THEN
         INSORT=.TRUE.
         DO 20 I=SSTART,LASTI,-1
            IF (A(I).LT.A(I+1)) THEN
                TEMP=A(I)
                A(I)=A(I+1)
                A(I+1)=TEMP
                INSORT=.FALSE.
                LASTS=I
             END IF
 20        CONTINUE
           LASTI=LASTS+1
           GO TO 10
       END IF
       RETURN
       END
```

```
C*************************************************************
C
      SUBROUTINE STRPOF
C
C*************************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,MSTR75,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300),
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85TTOTRY(300)
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
      COMMON RANARY(9000),DSEED,TOT,ME,LE,TETYY,CNTEM
      N=200
      JJUMP=0
      IJUMP=0
      IBANG=0
      BIGBV=0.0
      IJACK=I
      BIGER=0.0
      SIMPER=0.0
      TYSKP=TOT
 33   SKIP=TYSKP/N
      IBANG=0
      DO 10 LIP=1,IJACK
      IF (BVARY(LIP).GT.SKIP) THEN
         J=LIP
         IBANG=1
         GO TO 34
      END IF
 10   CONTINUE
      IF (IBANG.EQ.0) GO TO 35
 34   DO 20 K=J,IJACK
         IJUMP=IJUMP+1
         JJUMP=JJUMP+1
         BIGBV=BIGBV+BVARY(K)
         BIGER=BIGER+ERRARY(K)
         SIMPER=SIMPER+ERRARY(K)
 20   CONTINUE
      TYSKP=TOT-BIGBV
      N=N-JJUMP
      IJACK=I-IJUMP
      JJUMP=0
      IF (IBANG.GT.0) GO TO 33
 35   RETURN
      END
```

```
C****************************************************************
C
      SUBROUTINE INFO
C
C****************************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300)
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
      COMMON RANARY(9000),DSEED,TOT,ME,LE,TETYY,CNTEM
      NX=0
      TE=0.0
      TOT=0.0
      M=0
      TYE=0.0
      TELI=0.0
      TEDV=0.0
      TBR=0.0
      TETYY=0.0
      DO 1 JACK=1,I
      NX=NX+1
      TE=TE+ERRARY(JACK)
      TOT=TOT+BVARY(JACK)
      IF (ERRARY(JACK).NE.0.0) THEN
         M=M+1
         TYE=TYE+BVARY(JACK)
      END IF
 1    CONTINUE
      TELI=FLOAT(M)/FLOAT(NX)
      TEDV=TYE/TOT
      TBR=TE/TYE
      TETYY=TE/TOT
      WRITE(9,20) ISDYPP,M,NX,TOT,TYE
      WRITE(9,21) TE,TELI,TEDV,TBR,TETYY
 20   FORMAT(1X,3(I5,2X),2(F14.4,2X))
 21   FORMAT(1X,F14.2,4(F14.6,1X))
      RETURN
      END
C****************************************************************
C
      SUBROUTINE BOUND1
C
C****************************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
```

```
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300)
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
      COMMON RANARY(9000),DSEED,TOT,ME,LE,TETYY,CNTEM
      REAL STR90, STR85, MSTR90, MSTR85
      BP90=2.31
      BP85=1.90
      DO 10 IZ=1,N
         XMLE=XMLE+A(IZ)
         PGW90=PGW90+(B90(IZ)*A(IZ))
         PGW85=PGW85+(B85(IZ)*A(IZ))
 10   CONTINUE
      FN=FLOAT(N)
      STR90=(BP90+XMLE+PGW90)*TYSKP/FN+SIMPER
      STR85=(BP85+XMLE+PGW85)*TYSKP/FN+SIMPER
      MSTR90=(TOT-SAMPBV)*(BP90+XMLE+PGW90)/FN+SAMPER
      MSTR85=(TOT-SAMPBV)*(BP85+XMLE+PGW85)/FN+SAMPER
      RETURN
      END
C***********************************************************
C
      SUBROUTINE BOUND2
C
C***********************************************************
      COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
      COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
      COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
      COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
      COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
      COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
      COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
      COMMON AAVARY(300),EERARY(300),TTNTRY(300)
      COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
      COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP
      COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
      COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
      COMMON RANARY(9000),DSEED,TOT,ME,LE,TETYY,CNTEM
      REAL P,D1,D2,X,FIRST(5),MCS90(5),MMC190(5),MMC290(5)
      REAL MMC390(5),MCS85(5),MMC185(5),MMC285(5),MMC385(5)
      INTEGER IER
      FN=FLOAT(N)
      DO 12 IW=1,N
         IF (A(IW).GT.0.0) IM=IM+1
         TOTANT=TOTANT+A(IW)
```

```
 12     CONTINUE
        IF (IM.EQ.0) THEN
           TBAR=0.0
        ELSE
           TBAR=TOTANT/FLOAT(N)
        END IF
        DO 13 IG=1,5
           FIRST(IG)=((((FLOAT(IM)*TBAR)+
     *     (BMU(IG)-1)*TMU(IG))/
     *     ((API(IG)/PI(IG))+FN))*(FLOAT(IM)+API(IG))/
     *     (FLOAT(IM)+BMU(IG)))
           D1=2*(FLOAT(IM)+API(IG))
           D2=2*(FLOAT(IM)+BMU(IG))
           P=.90
           CALL MDFI (P,D1,D2,X,IER)
           CS90(IG)=FIRST(IG)*X*TYSKP+SIMPER
           MCS90(IG)=FIRST(IG)*X*(TOT-SAMPBV)+SAMPER
           MMC190(IG)=MCS90(IG)*1.05
           MMC290(IG)=MCS90(IG)*1.10
           MMC390(IG)=MCS90(IG)*1.20
           P=.85
           CALL MDFI (P,D1,D2,X,IER)
           CS85(IG)=FIRST(IG)*X*TYSKP+SIMPER
           MCS85(IG)=FIRST(IG)*X*(TOT-SAMPBV)+SAMPER
           MMC185(IG)=MCS85(IG)*1.05
           MMC285(IG)=MCS85(IG)*1.10
           MMC385(IG)=MCS85(IG)*1.20
  13    CONTINUE
        RETURN
        END
C****************************************************************
C
        SUBROUTINE INITA
C
C****************************************************************
        COMMON A(200),BMU(5),API(5),PI(5),TMU(5),B90(200)
        COMMON B85(200),N,SKIP,BVARY(9000),AVARY(9000)
        COMMON ERRARY(9000),TNTARY(9000),TOTARY(9000)
        COMMON JZZ,CS90(5),MCS90(5),MMC190(5),MMC290(5)
        COMMON MMC390(5),CS85(5),MCS85(5),MMC185(5),MMC285(5)
        COMMON MMC385(5),IM,TOTANT,TBAR,STR90,STR85
        COMMON MSTR90,MSTR85,BBVARY(300),INDEX(9000)
        COMMON AAVARY(300),EERARY(300),TTNTRY(300)
        COMMON IINDEX(300),PGW90,PGW85,BP90,BP85,TTOTRY(300)
        COMMON XMLE,TELI,TEDV,TBR,IGY,ISDYPP,TYSKP
        COMMON SIMPER,BIGER,BIGBV,I,SAMPER,SAMPBV,ITOOT,TYE
        COMMON TE,NX,M,FN,J,LERA(6),TL(4),TH(4),MID,CNTIT
        COMMON RANARY(9000),DSEED,TOT,ME,LE,TETYY,CNTEM
C       B VALUES
        BMU(1)=18.00
        BMU(2)=2.0625
        BMU(3)=2.4444
```

```
      BMU(4)=3.00
      BMU(5)=6.00
C     A VALUES
      API(1)=.0625
      API(2)=1.00
      API(3)=1.00
      API(4)=1.00
      API(5)=1.00
C     ERROR RATES
      PI(1)=.05
      PI(2)=.20
      PI(3)=.20
      PI(4)=.20
      PI(5)=.20
C     MEAN TAINTS
      TMU(1)=.40
      TMU(2)=.05
      TMU(3)=.10
      TMU(4)=.20
      TMU(5)=.40
C     PRECISION GAP WIDENING VALUES:  90% CONFIDENCE LEVEL
      B90(1)=.58
      B90(2)=.44
      B90(3)=.36
      B90(4)=.31
      B90(5)=.28
      B90(6)=.26
      B90(7)=.
      B90(8)=.22
      B90(9)=.21
      B90(10)=.20
      B90(11)=.19
      B90(12)=.19
      B90(13)=.17
      B90(14)=.17
      B90(15)=.17
      B90(16)=.16
      B90(17)=.15
      B90(18)=.15
      B90(19)=.15
      B90(20)=.14
      B90(21)=.14
      B90(22)=.13
      B90(23)=.14
      B90()=.13
      B90(25)=.13
      B90(26)=.14
      B90(27)=.12
      B90(28)=.12
      B90(29)=.12
      B90(30)=.12
      B90(31)=.12
```

```
      B90(32)=.12
      B90(33)=.12
      B90(34)=.12
      B90(35)=.12
      B90(36)=.11
      B90(37)=.11
      B90(38)=.11
      B90(39)=.11
      DO 210 JC1=40,50
         B90(JC1)=.10
 210  CONTINUE
      DO 220 JC2=51,59
         B90(JC2)=.09
 220  CONTINUE
      DO 230 JC3=60,79
         B90(JC3)=.08
 230  CONTINUE
      DO 0 JC4=80,94
         B90(JC4)=.07
 0    CONTINUE
      DO 250 JC5=95,110
         B90(JC5)=.06
 250  CONTINUE
      DO 260 JC6=111,125
         B90(JC6)=.05
 260  CONTINUE
      DO 270 JC7=126,140
         B90(JC7)=.04
 270  CONTINUE
      DO 280 JC8=141,155
         B90(JC8)=.03
 280  CONTINUE
      DO 290 JC9=156,170
         B90(JC9)=.02
 290  CONTINUE
      DO 300 JC10=171,185
         B90(JC10)=.01
 300  CONTINUE
      DO 310 JC11=186,200
         B90(JC11)=0.00
 310  CONTINUE
C     PRECISION GAP WIDENING VALUES:  85% CONFIDENCE LEVEL
      B85(1)=.48
      B85(2)=.35
      B85(3)=.29
      B85(4)=.25
      B85(5)=.23
      B85(6)=.21
      B85(7)=.19
      B85(8)=.18
      B85(9)=.17
      B85(10)=.17
```

```
      B85(11)=.15
      B85(11)=.15
      B85(12)=.14
      B85(13)=.14
      B85(14)=.13
      B85(15)=.13
      B85(16)=.13
      B85(17)=.12
      B85(18)=.12
      B85(19)=.11
      B85(20)=.11
      B85(21)=.11
      B85(22)=.11
      B85(23)=.11
      B85()=.11
      B85(25)=.10
      B85(26)=.10
      B85(27)=.10
      B85(28)=.10
      B85(29)=.10
      DO 110 JA1=30,40
         B85(JA1)=.09
110   CONTINUE
      DO 120 JA2=41,49
         B85(JA2)=.08
120   CONTINUE
      DO 130 JA3=50,69
         B85(JA3)=.07
130   CONTINUE
      DO 140 JA4=70,89
         B85(JA4)=.06
140   CONTINUE
      DO 150 JA5=90,105
         B85(JA5)=.05
150   CONTINUE
      DO 160 JA6=106,125
         B85(JA6)=.04
160   CONTINUE
      DO 170 JA7=126,140
         B85(JA7)=.03
170   CONTINUE
      DO 180 JA8=141,155
         B85(JA8)=.02
180   CONTINUE
      DO 190 JA9=156,175
         B85(JA9)=.01
190   CONTINUE
      DO 200 JA10=176,200
         B85(JA10)=0.00
200   CONTINUE
70    CONTINUE
      RETURN
      END
```

Appendix B: Study Population Characteristics

Study Pop	ER	L/H Taint	T_{LI}	T_t	$T_{Y(e)}$	T_e	EAI
1	.8	.1/.05	.80	.08	7,729,232	609,642	.06432
2	.8	.2/.1	.80	.15	7,729,232	1,161,342	.12081
3	.8	.4/.2	.80	.31	7,729,232	2,412,078	.25091
4	.8	.8/.4	.80	.46	7,729,232	3,584,906	.37291
5	.25	.1/.05	.25	.09	2,363,239	209,322	.02177
6	.25	.2/.1	.25	.16	2,363,239	388,310	.04039
7	.25	.4/.2	.25	.31	2,363,239	733,106	.07626
8	.25	.8/.4	.25	.46	2,363,239	1,092,029	.11360
9	.10	.1/.05	.08	.08	814,558	67,947	.00707
10	.10	.2/.1	.08	.16	814,558	132,154	.01375
11	.10	.4/.2	.08	.31	814,558	250,690	.02608
12	.10	.8/.4	.08	.45	814,558	369,018	.03839
13	.05	.1/.05	.05	.10	458,759	43,952	.00457
14	.05	.2/.1	.05	.18	458,759	81,393	.00847
15	.05	.4/.2	.05	.29	458,759	131,147	.01364
16	.05	.8/.4	.05	.43	458,759	196,598	.02045
17	.01	.1/.05	.02	.05	146,152	7,942	.00083
18	.01	.2/.1	.02	.10	146,152	13,951	.00145
19	.01	.4/.2	.02	.37	146,152	54,009	.00562
20	.01	.8/.4	.02	.29	146,152	42,460	.00442
21	.005	.1/.05	.004	.06	34,431	2,086	.00022
22	.005	.2/.1	.004	.19	34,431	6,433	.00067
23	.005	.4/.2	.004	.34	34,431	11,646	.00121
24	.005	.8/.4	.004	.48	34,431	16,365	.00170

Appendix C: Tables of Bound Results by EAI Category

EAI Category: Low (6 study populations)

Bound: CS90

	π_0	.05	.20
	σ_π	.20	.20
μ_0	σ_μ		
.05	.20		1/6 .167
.10	.15		4/6 .705
.20	.20		6/6 1.00
.40	.20		6/6 1.00
	.10	1/6 .683	

Key: Each number grouping represents--

study populations adequately covered   mean coverage

EAI Category: Low (6 study populations)

Bound: MCS90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		1/6 .190 1.089
.10	.15		3/6 .668 1.145
.20	.20		6/6 1.00 1.183
.40	.20		6/6 1.00 1.207
	.10	0/6 .598 1.201	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Low (6 study populations)

Bound: M1M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		1/6 .205 1.037
.10	.15		3/6 .685 1.090
.20	.20		6/6 1.00 1.127
.40	.20		6/6 1.00 1.150
	.10	0/6 .598 1.143	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Low (6 study populations)

Bound: M2M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		1/6 .209 .990
.10	.15		4/6 .727 1.041
.20	.20		6/6 1.00 1.076
.40	.20		6/6 1.00 1.098
	.10	0/6 .598 1.091	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Low (6 study populations)

Bound: M3M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		1/6 .235 .908
.10	.15		4/6 .750 .954
.20	.20		6/6 1.00 .986
.40	.20		6/6 1.00 1.006
	.10	1/6 .683 1.000	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Low (6 study populations)

Bound: CS85

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		1/6 .167
.10	.15		2/6 .595
.20	.20		5/6 .912
.40	.20		6/6 1.00
	.10	0/6 .598	

Key: Each number grouping represents--

study populations adequately covered   mean coverage

EAI Category: Low (6 study populations)

Bound: MCS85

μ_0	σ_μ	π_0 = .05 σ_π = .20	π_0 = .20 σ_π = .20
.05	.20		1/6 .187 1.073
.10	.15		1/6 .407 1.133
.20	.20		5/6 .912 1.176
.40	.20		6/6 1.00 1.205
	.10	0/6 .598 1.196	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Low (6 study populations)

Bound: M1M85

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		1/6 .188 1.022
.10	.15		2/6 .559 1.079
.20	.20		5/6 .912 1.120
.40	.20		6/6 1.00 1.147
	.10	0/6 .598 1.139	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Low (6 study populations)

Bound: M2M85

μ_0	σ_μ	π_0 .05 σ_π .20	π_0 .20 σ_π .20
.05	.20		1/6 .191 .975
.10	.15		2/6 .613 1.030
.20	.20		5/6 .912 1.069
.40	.20		6/6 1.00 1.095
	.10	0/6 .598 1.087	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Low (6 study populations)

Bound: M3M85

	π_0	.05	.20
	σ_π	.20	.20
μ_0	σ_μ		
.05	.20		1/6 .210 .894
.10	.15		2/6 .656 .944
.20	.20		5/6 .912 .980
.40	.20		6/6 1.00 1.004
	.10	0/6 .598 .997	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Medium (12 study populations)

Bound: CS90

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		0/12 .000
.10	.15		0/12 .000
.20	.20		0/12 .073
.40	.20		5/12 .431
	.10	6/12 .729	

Key: Each number grouping represents--

study populations adequately covered   mean coverage

EAI Category: Medium (12 study populations)

Bound: MCS90

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		0/12 .000 .646
.10	.15		0/12 .000 .719
.20	.20		0/12 .038 .832
.40	.20		4/12 .415 1.017
	.10	5/12 .696 1.079	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Medium (12 study populations)

Bound: M1M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/12 .000 .587
.10	.15		0/12 .000 .653
.20	.20		0/12 .077 .756
.40	.20		4/12 .437 .924
	.10	6/12 .743 .981	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Medium (12 study populations)

Bound: M2M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/12 .000 .587
.10	.15		0/12 .001 .653
.20	.20		0/12 .082 .756
.40	.20		5/12 .485 .924
	.10	6/12 .784 .981	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Medium (12 study populations)

Bound: M3M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/12 .000 .538
.10	.15		0/12 .008 .599
.20	.20		1/12 .110 .693
.40	.20		5/12 .566 .847
	.10	7/12 .837 .899	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Medium (12 study populations)

Bound: CS85

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/12 .000
.10	.15		0/12 .000
.20	.20		0/12 .015
.40	.20		4/12 .404
.40	.10	7/12 .657	

Key: Each number grouping represents--

study populations adequately covered mean coverage

EAI Category: Medium (12 study populations)

Bound: MCS85

μ_0	σ_μ	π_0 = .05 σ_π = .20	π_0 = .20 σ_π = .20
.05	.20		0/12 .000 .626
.10	.15		0/12 .000 .697
.20	.20		0/12 .008 .811
.40	.20		4/12 .400 1.003
	.10	6/12 .639 1.069	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Medium (12 study populations)

Bound: M1M85

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		0/12 .000 .596
.10	.15		0/12 .000 .663
.20	.20		0/12 .029 .772
.40	.20		4/12 .414 .955
	.10	6/12 .680 1.018	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Medium (12 study populations)

Bound: M2M85

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/12 .000 .569
.10	.15		0/12 .000 .633
.20	.20		0/12 .062 .737
.40	.20		4/12 .432 .912
	.10	7/12 .717 .972	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Medium (12 study populations)

Bound: M3M85

μ_0	σ_μ	π_0 .05 σ_π .20	π_0 .20 σ_π .20
.05	.20		0/12 .000 .521
.10	.15		0/12 .006 .581
.20	.20		1/12 .082 .676
.40	.20		4/12 .504 .836
	.10	8/12 .799 .891	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: High (4 study populations)

Bound: CS90

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		0/4 .070
	ν		
.10	.15		0/4 .077
.20	.20		0/4 .094
.40	.20		0/4 .269
	.10	2/4 .478	

Key: Each number grouping represents--

study populations adequately covered   mean coverage

EAI Category: High (4 study populations)

Bound: MCS90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/4 .022 .915
.10	.15		0/4 .023 .917
.20	.20		0/4 .034 .924
.40	.20		0/4 .154 .957
	.10	1/4 .425 1.006	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: High (4 study populations)

Bound: M1M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/4 .087 .872
.10	.15		0/4 .091 .874
.20	.20		0/4 .109 .880
.40	.20		0/4 .266 .911
	.10	1/4 .475 .958	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: High (4 study populations)

Bound: M2M90

μ_0	σ_μ	π_0: .05 σ_π: .20	π_0: .20 σ_π: .20
.05	.20		0/4 .177 .832
.10	.15		0/4 .186 .834
.20	.20		0/4 .200 .840
.40	.20		0/4 .359 .870
	.10	2/4 .497 .915	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: High (4 study populations)

Bound: M3M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/4 .339 .763
.10	.15		0/4 .347 .764
.20	.20		0/4 .375 .770
.40	.20		1/4 .469 .797
	.10	2/4 .509 .839	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: High (4 study populations)

Bound: CS85

μ_0	σ_μ	π_0: .05, σ_π: .20	π_0: .20, σ_π: .20
.05	.20		0/4 .034
.10	.15		0/4 .036
.20	.20		0/4 .058
.40	.20		0/4 .205
	.10	1/4 .456	

Key: Each number grouping represents--

study populations adequately covered   mean coverage

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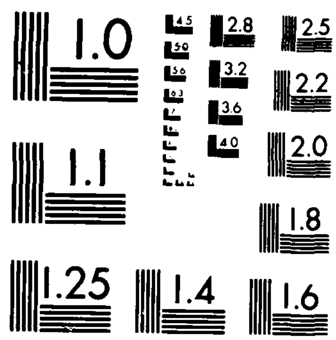

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EAI Category: High (4 study populations)

Bound: MCS85

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		0/4 .013 .907
.10	.15		0/4 .013 .909
.20	.20		0/4 .018 .916
.40	.20		0/4 .118 .949
	.10	1/4 .397 1.000	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: High (4 study populations)

Bound: M1M85

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		0/4 .058 .864
.10	.15		0/4 .062 .866
.20	.20		0/4 .079 .872
.40	.20		0/4 .219 .904
	.10	1/4 .451 .952	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: High (4 study populations)

Bound: M2M85

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/4 .128 .825
.10	.15		0/4 .133 .827
.20	.20		0/4 .163 .832
.40	.20		0/4 .315 .863
	.10	2/4 .488 .909	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: High (4 study populations)

Bound: M3M85

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		0/4 .297 .756
.10	.15		0/4 .308 .758
.20	.20		0/4 .330 .763
.40	.20		0/4 .446 .791
	.10	2/4 .505 .833	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Very High (2 study populations)

Bound: CS90

μ_0	σ_μ	π_0: .05, σ_π: .20	π_0: .20, σ_π: .20
.05	.20		0/2 .062
.10	.15		0/2 .061
.20	.20		0/2 .064
.40	.20		0/2 .084
	.10	0/2 .173	

Key: Each number grouping represents--

study populations adequately covered mean coverage

EAI Category: Very High (2 study populations)

Bound: MCS90

μ_0	σ_μ	π_0 .05, σ_π .20	π_0 .20, σ_π .20
.05	.20		0/2 .039 1.020
.10	.15		0/2 .037 1.020
.20	.20		0/2 .039 1.021
.40	.20		0/2 .040 1.023
	.10	0/2 .067 1.028	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Very High (2 study populations)

Bound: M1M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/2 .110 .972
.10	.15		0/2 .108 .972
.20	.20		0/2 .111 .972
.40	.20		0/2 .138 .974
	.10	0/2 .242 .979	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Very High (2 study populations)

Bound: M2M90

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/2 .320 .928
.10	.15		0/2 .314 .927
.20	.20		0/2 .320 .928
.40	.20		0/2 .379 .930
	.10	0/2 .546 .934	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Very High (2 study populations)

Bound: M3M90

μ_0	σ_μ	π_0 .05 σ_π .20	π_0 .20 σ_π .20
.05	.20		0/2 .795 .850
.10	.15		0/2 .794 .850
.20	.20		0/2 .801 .850
.40	.20		0/2 .852 .852
	.10	2/2 .946 .856	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Very High (2 study populations)

Bound: CS85

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/2 .036
.10	.15		0/2 .035
.20	.20		0/2 .035
.40	.20		0/2 .044
.40	.10	0/2 .097	

Key: Each number grouping represents--

study populations adequately covered   mean coverage

EAI Category: Very High (2 study populations)

Bound: MCS85

μ_0	σ_μ	π_0: .05, σ_π: .20	π_0: .20, σ_π: .20
.05	.20		0/2 .013 1.016
.10	.15		0/2 .013 1.016
.20	.20		0/2 .013 1.016
.40	.20		0/2 .020 1.018
	.10	0/2 .034 1.023	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Very High (2 study populations)

Bound: M1M85

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/2 .067 .967
.10	.15		0/2 .067 .967
.20	.20		0/2 .068 .968
.40	.20		0/2 .081 .970
	.10	0/2 .140 .975	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Very High (2 study populations)

Bound: M2M85

		π_0	.05	.20
		σ_π	.20	.20
μ_0	σ_μ			
.05	.20			0/2 .214 .924
.10	.15			0/2 .212 .923
.20	.20			0/2 .217 .924
.40	.20			0/2 .263 .926
	.10		0/2 .402 .930	

Key: Each number grouping represents--

study populations adequately covered mean coverage
mean rel tightness wrt unmodified C&S bound

EAI Category: Very High (2 study populations)

Bound: M3M85

μ_0	σ_μ	π_0 = .05, σ_π = .20	π_0 = .20, σ_π = .20
.05	.20		0/2 .699 .847
.10	.15		0/2 .699 .847
.20	.20		0/2 .706 .847
.40	.20		0/2 .771 .849
	.10	2/2 .886 .853	

Key: Each number grouping represents--

study populations adequately covered   mean coverage
mean rel tightness wrt unmodified C&S bound

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The purpose of this research was to examine robustness, mean relative tightness, coverage, and power of selected unmodified and modified Cox and Snell and Stringer error limit bounds. The simulation was performed by repetitive sampling from an accounting population with various known book value and error distributions. Additional modifications to the selected Cox and Snell bounds was done by incrementally loosening the bounds by 5, 10, and 20 percent in a search for bounds with better performance characteristics.

There were several conclusions that could be made from this research. The modified Cox and Snell bounds can achieve high coverages for accounting populations with low error amount intensities (EAI) with significant increases in mean relative tightness over unmodified Cox and Snell bounds. The Stringer and Cox and Snell bounds can still achieve high coverages with significant improvements in mean relative tightness when the nominal confidence level is lowered from 90% to 85%. Only minor changes in prior probability parameter settings materially affect the performance of Cox and Snell bounds. And, in accounting populations with low EAI, the selected Cox and Snell bounds are conservative.

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