SIMULATION - AN ADVANTAGE FOR ACCOUNTING RESEARCH

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ABSTRACT

The use of accounting data in research has presented some problems in the past. Simulation has been used in other areas of accounting and the next logical extension is the use of simulated accounting populations. An example of a situation involving simulation and some of the factors involved is presented to illustrate the technique.

INTRODUCTION

One of the problems of research is the availability of data. For accountants, this problem in relation to accounting populations is especially acute. Finding "live' information for research purposes is a difficult task at best. If the 'live" data is available, establishing familiarity with this data is a complex task. Simulation techniques can provide an acceptable alternative to the problem of employing accounting data **in** research. The purpose of this paper is to justify the use of the simulation procedure and to provide an illustration of a design for several accounting populations.

JUSTIFICATION

Hammersley and Handscomb, in a monograph on Monte Carlo methods, mentioned that one of the principle forms of Monte Carlo Is characterized by a fairly simple general structure overlaid with a mass of small and particular details [2, p. 43]. Accounting populations may be classified in this pattern. The actual populations are not easily studied as general models, but populations may easily be simulated. In addition to the ease of formulation, Monte Carlo methods also have the advantages of operating in a totally controlled environment, of omitting extraneous, undocumented variables, and of monitoring the situation with certainty.

Specifically within the field of accounting, Monte Carlo studies have been applied and accepted by the professional community. Mattesich [4, 5] introduced simulation to the topic of budgeting. In justifying his use of simulation, Mattesich compared the technique to the use of a wind tunnel by a physical scientist. In the physical sciences, one cannot always control the environment so an artificial, environment (i.e., the wind tunnel) is created. Likewise, in behavioral sciences, the environment is unpredictable, thus the behavioral scientist needs some tool to create a controlled surrounding for his experiments. The tool, Mattesich suggested, is simulation. 'Such experiments (simulations) . . . do enable. . . the mental reproduction of a large number of alternative situations and thus help to determine satisfactory if not approximately optimal solutions." [5, p. 386]

Neter and Loebbecke [61 used 'real accounting data as the base for their study of the behavior of major statistical estimators. However, the 'study" populations appeared to have been manipulated with the use of simulation techniques. Neter and Loebbecke explained:

> "...several study populations with a variety of error rates were created. This was done by utilizing the error pattern actually found to assign errors at random to the audit emits in the populations to achieve the specified error rate." [6, p. 71

No further detail was presented into the process of assigning additional errors but the technique appears to be a simulation procedure.

In 1976, Magee used simulation procedures to analyze alternative cost variance investigation models. Magee noted that although analytic methods are usually preferable, these methods are not always feasible. However, in using simulation and "by using the same sequence of random members, the various models can be tested on similar.. .data, facilitating comparisons among models." [3, p. 532]

Thus, the use of simulation (specifically, Monte Carlo methods) has been accepted and approved, particularly in situations of voluminous data and excessively detailed models.

SIMULATION DESIGN EXAMPLE

In developing a simulation (and in presenting this example) clear statement should be made as to the use of the simulation and the form the simulated information should take. For this example the accounting populations are being simulated to test the effects of errors in the populations.

In the last ten years, researchers have advocated the use of operations research techniques and statistical analyses in conjunction with accounting information. However, while the assumptions of the models have been stated, very little testing has been performed to see if accconting populations conform to the assumptions or if unaudited populations (which may contain errors) react differently to these models.

Thus this example is designed to provide two simulated populations: the first is the audited accounting population in which an auditor (Certified Public Accountant) would perceive no material errors; and a second population, referred to as the book value population. The book value population does contain material errors.

The audited population is simulated first and used as the base for the book value population. In defining the audited population, the study by Neter and Loebbecke [6] is the prime resource. No other studies of actual accounting populations surfaced in preparation for the simulation. Neter and Loebbecke examined four accounting populations and all populations were in the gamma distributional form. The other factors associated with the actual populations varied a great deal: the mean, the variance, the kertosis, and the skewness. Thus, the simulation used the gamma distribution for generating the audited population values but did not follow any particular pattern in denoting the size of the distribution. A visual check was made between the gamma deviates and the distribution shown in Neter and Loebbecke's [6, p. 131 study and a simple chi-square confirmed that no significant difference existed between the generated gamma distribution and a theoretical gamma distribution.

Simulating the book value population is a more difficult task because of the number of possible variations. Four of the parameters were allowed to range within certain limits to conform to the actual populations studied by Neter and Loebbecke.

The first variable to be considered is the percentage of the population containing errors. In Neter and Loebbecke's [6] study of four "real" accounting populations, they found that the number of items recorded in error ranged from 5% of the population to 71% of the population. Thus the book value populations simulated to compare with audited populations contained one of the following four rates of error occurrence: 5%, 10% 30% or 70%.

The mathematical form of the errors is the second variable included in this list. The errors observed by Neter and Loebbecke [6] show no clear tendency to either a multiplicative or an additive relationship with the variable containing the errors. In some populations that Neter and Loebbecke studied, the error value increased as the true (audited) value increased (a multiplicative relationship between the true value and the error value). In other populations, the error value did not fluctuate significantly with the true value (an additive relationship between the true value and the error values). Neter and Loebbecke point out that the errors studied were not sufficient evidence upon which to form solid conclusions; in light of this caveat, the variable f error form is examined as either a simple multiplicative relationship or a simple additive relationship. The form of the multiplicative relationship may be depicted as:

The distributional form of the error may prove to be a significant factor. Again, the only available information of the distribution of errors occurring in accounting populations

$$\hat{X}_i = X_i + X_i E_1 \qquad (1)$$

where

X_i is the audited value or true value,

$\hat{X}_i$ is the book value, and

E_1 is the random error term expressed as a percent.

The additive relationship may be shown as:

$$\hat{X}_i = X_i + E_2 \qquad (2)$$

where

E_2 is the random error term expressed in the same denomination as X_i.

is contained in the study by Neter and Loebbecke. Although the errors studied were insufficient for forming conclusions, the patterns of the errors suggest some possible distributional forms. The errors in the Neter and Loebbecke study tended to be either equally understatements and overstatements, or all overstatements. Two typical distributions, representative of equal under- and overstatements, are the normal distribution and the uniform distribution. For cases involving mostly overstatements, a positively skewed distribution was indicated, and for purposes of the simulation, the gamma distribution was chosen as a suitable representation.

Finally, the size of the errors must be determined. The distributions and for-ms of the errors are allowed to vary, and variations in the size of the errors are permitted within the bounds of the distributions. However, all errors considered in the simulation are of a size that is defined as material. A material error is considered to be at least a ten percent difference between the audited (true) value and the book value. All errors that are not material are regenerated until the error is of a material size. Accountants have expressed a decided "disinterest" in errors that are nonmaterial [1] and thus the logic in omitting nonmaterial errors.

This procedure was employed in a study of the effects of accounting populations on the use of regression analysis and the data (the accounting populations) were more than satisfactory. However, several warnings are imperative when employing this technology.

Many assumptions are made in simulating the populations. Although logical justifications were presented for the assumptions, this is not assurance that the assumptions are always warranted. For instance, all the populations studied and reported by Neter and Loebbecke [61 were either of inventories or accounts receivable. Perhaps the assumption of a gamma distribution is only valid in regard to these two populations. Another situation may pair accounting populations with more mundane measures (GNP, days in a month) which are clearly not gamma distributions.

The usage of a random number seed can also be misused. The comparisons to be tested in a simulation must be predetermined. If the comparisons are to be made within the simulated information group, the choice or variety of random number seeds is not of prime importance. However, if comparisons are made between simulated information groups, the independence of the simulation information groups can be threatened by the improper use of random number seeds.

In summation, the use of simulated accounting populations in accounting research has been, and will continue to be, an excellent alternative to "live" data. The user, however, should acquaint himself with the special properties of the 'live data as well as the intricacies of simulation techniques before embarking on a major simulation undertaking in the field of ac- counting research.

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