

COMPARATIVE EFFICIENCY OF SAMPLING PLANS (ILLUSTRATION – APPLE TREES)



**ECONOMICS, STATISTICS, AND
COOPERATIVES SERVICE**

**U.S. DEPARTMENT
OF AGRICULTURE**

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By

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PREFACE

This publication is regarded by the author as supplementary training material for students who are familiar with, or are studying, elementary theory of sampling including stratification, cluster sampling, ratio and regression estimation, sampling with probability proportional to size, and multiple-stage sampling. After studying sampling methods one at a time, it is important to get a unified view of the several methods and the conditions under which they have about the same or different variances.

In sampling various populations we quite often find two or more techniques that are roughly equal in efficiency and reduce sampling variance about as much as possible. Administrative feasibility, costs, and freedom from potential bias are important criteria for selecting a sampling plan and become primary criteria when the choice is among plans having small differences in sampling variance.

Ability to prejudge accurately the efficiency of alternative sample designs with reference to various survey objectives and populations is important. Such ability comes from experience and detailed study of alternative techniques of sampling a population and of making estimates. Quite often only two or three alternatives are compared in an analysis because of limitations of data or only a few alternatives are of interest. In this publication many alternative

sampling and estimation plans are applied to a small population of apple trees and the results are recorded in tables for comparative purposes. The focus of attention is on the magnitude of the differences in efficiency in relation to the patterns of variation that exist.

For some readers, parts of the presentation are probably too detailed. However, it is important to understand fully the alternatives and to put mathematical expressions for estimators and their variances in forms that are most meaningful for comparative purposes. Exercises are distributed through the text.

Chapter I makes use of graphical, or geometrical, interpretations in the comparison of four alternative ways of using an auxiliary variable. There is a brief presentation of the relevant theory for each plan which is followed by a discussion of the plans including a numerical example. Sampling with probability proportional to size in comparison to other methods is of special interest. For comparison, a part of each variance formula is written as the sum of squares of deviations from a line.

Chapter II expands the comparisons made in Chapter I to include interactions in efficiency. For example, the comparative efficiency of sampling units of various size is related to the method of estimation and to stratification. Chapter III provides some further comparisons, but the emphasis is on how

theory and ingenuity solved an important problem in the sampling of fruit trees. Some comparisons involving two-stage sampling using apple trees as an example are included in Chapter IV.

This volume was written because it was a pleasure and because I always learn something from making comparisons like those contained herein.

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CHAPTER I
SIMPLE USES OF AN AUXILIARY VARIABLE

1.1 INTRODUCTION

Proficiency in the use of auxiliary information to reduce sampling variance is an important goal in the formulation of a sampling plan. In this chapter we will compare four alternative methods of using an auxiliary variable in the design of a sample or in the estimator and one without using an auxiliary variable, giving a total of five alternative methods. The methods discussed are commonly found in textbooks on sampling. It is important to know whether an auxiliary variable is worth using and how to use it most effectively. Achievement of greater efficiency in the use of an auxiliary variable is usually inexpensive compared to increasing sample size, but incorrect use could cause an increase rather than a decrease in sampling error.

For each of the five alternatives there is an estimator and the variance of each estimator can be expressed in a form that is suitable for interpretation of the sampling variance as a function of deviations of points from a line. The emphasis in this chapter is on simple dot charts as a useful aid to understanding or judging the comparative effectiveness of alternative methods in different situations. Special attention will be given to sampling with probability proportional to size and how it compares with other ways of using an auxiliary variable

including stratification and optimum allocation. After a review of notation, definitions, and theory, a numerical example will be presented which makes use of some data collected in a research project to develop techniques for estimating apple production.

Consider a population of N sampling units and let Y_1, \dots, Y_N represent the unknown values of Y and let X_1, \dots, X_N represent the known values of an auxiliary variable X . A sample is to be selected and the values of Y for the n su's (sampling units) in the sample, namely y_1, \dots, y_n , are to be obtained. The corresponding values of X for the su's in the sample are x_1, \dots, x_n . We assume that the objective is to estimate the

population mean, $\bar{Y} = \frac{\sum Y_i}{N}$. Also, in the interest of keeping the notation as simple as possible, let Y and X represent the population totals. That is, $Y = \sum Y_i$ and $X = \sum X_i$. This gives "Y", for example, a dual meaning as in "the characteristic Y" or as the total for the population. However, the meaning should be clear from the context.

A resume of the theory for each of the five alternatives, which will be called plans, is presented after a brief review of sampling with equal and unequal probabilities of selection.

1.1.1 EQUAL PROBABILITIES OF SELECTION

A sample obtained by selecting one su at a time, at random with equal probability and without replacement, is called a simple random sample. When the variance of Y in the

population is defined as

$$\sigma^2 = \frac{\sum (Y_i - \bar{Y})^2}{N} \quad (1.1)$$

the variance of the mean, \bar{y} , of a simple random sample of n is given by

$$V(\bar{y}) = \frac{N-n}{N-1} \frac{\sigma^2}{n} \quad (1.2)$$

If the variance of Y is defined as

$$S^2 = \frac{\sum (Y_i - \bar{Y})^2}{N-1} \quad (1.3)$$

and the variance of \bar{y} is

$$V(\bar{y}) = \frac{N-n}{N} \frac{S^2}{n} \quad (1.4)$$

In the discussion that follows, S^2 will be used as the definition of the variance of y .

The mean, \bar{y} , of a simple random sample is an unbiased

estimate of \bar{Y} and the variance, $s^2 = \frac{\sum (y_i - \bar{y})^2}{n-1}$, among su 's in the sample is an unbiased estimate of S^2 . Incidentally, the writer from a practical point of view advises use of the word "unbiased" with some caution. In the mathematical theory, the meaning of "unbiased" is usually clear, but in practice "unbiased estimate" is often misleading to persons who are interested in estimates from a survey and are unaware of the restricted meaning of the term.^{1/}

^{1/} See sections 4.4 and 4.5 of Expected Value of a Sample Estimate, Statistical Reporting Service, USDA, September 1974.

Exercise 1.1 Show that either definition of the variance among the N values of Y leads to the same answer for the variance of \bar{y} . That is, show that equations 1.2 and 1.4 are the same.

1.1.2 UNEQUAL PROBABILITIES OF SELECTION

Some sampling plans specify that sampling units be selected with pps (probability proportional to size). For simplicity, sampling with replacement is assumed.

It is often very important to make a clear distinction between the probability of selecting the i^{th} su of a population when a particular random draw is made and the probability of the i^{th} su being included in a sample. To help make the distinction clear, the letter "P" or "p" will be used to represent selection probability and "f" will represent inclusion probability, that is, the probability of any given su being in the sample. When simple random sampling is applied, each su has a probability equal to $\frac{n}{N}$ of being in the sample. That is, the inclusion probability, f , is equal to $\frac{n}{N}$ for simple random sampling.

With regard to sampling with pps and replacement, let P_1, P_2, \dots, P_N be the set of selection probabilities for the N su's in the population. It is specified that $\sum_{i=1}^N P_i = 1$. Thus, "selecting a sample with probabilities proportional to X_i " means that $P_i = \frac{X_i}{\sum_{i=1}^N X_i}$ where $X = \sum_{i=1}^N X_i$. Since the sampling is with replacement, the selection probabilities remain constant from one random draw to another.

The unbiased estimator of \bar{Y} for a sample of n is

$$\bar{y} = \left(\frac{1}{N}\right) \left(\frac{1}{n}\right) \sum^n \frac{y_i}{p_i} \quad (1.5)$$

In the estimator, i is an index of the n random draws because the same su might be selected more than once. To illustrate, if on the 4th draw su number 15 in the population is selected, y_4 and p_4 are equal to Y_{15} and P_{15} . And if the 15th su is selected again on the 12th draw, y_{12} and p_{12} are equal to Y_{15} and P_{15} . In practice, techniques for avoiding the selection of the su more than once are usually introduced but such techniques are for later consideration.

Each of the n values of $\frac{y_i}{p_i}$ in Eq. 1.5 is an unbiased estimate of the population total. Thus, $\left(\frac{1}{n}\right) \sum^n \frac{y_i}{p_i}$ is a simple average of n independent, unbiased estimates of Y , and $\left(\frac{1}{N}\right)$ appears in Eq. 1.5 so \bar{y} will be an estimator of \bar{Y} instead of the population total.

The variance of \bar{y} , Eq. 1.5, is

$$V(\bar{y}) = \frac{\sigma^2}{n} \quad (1.6)$$

where
$$\sigma^2 = \left(\frac{1}{N^2}\right) \sum^N P_i \left(\frac{Y_i}{P_i} - Y\right)^2 = \left(\frac{1}{N^2}\right) \sigma_t^2 \quad (1.7)$$

and
$$Y = \frac{1}{N} \sum^N Y_i$$

Is Eq. 1.6 reasonable? Study the estimator. For any given value of i , $\frac{y_i}{p_i}$ in repeated sampling is a random variable which has an expected value equal to the population total, Y .

By definition, the variance of $\frac{y_i}{p_i}$ is

$$\sigma_t^2 = \sum P_i \left(\frac{Y_i}{P_i} - Y \right)^2$$

where i is the index to the N su's in the population. In the

estimator, $\frac{1}{n} \sum \frac{y_i}{p_i}$ is the average of n independent estimates;

therefore, the variance of this average is $\frac{\sigma_t^2}{n}$. And, since we

are interested in estimating \bar{Y} rather than Y , σ_t^2 must be divided by N^2 as shown in Eq. 1.7.

1.2 RESUME OF THEORY FOR FIVE PLANS ^{2/}

As discussed above, we will use S^2 , Eq. 1.3, as the definition of the population variance for simple random sampling with replacement and σ^2 , Eq. 1.7, is the definition of population variance for sampling with pps and replacement. Notice that, when the P_i all equal $\frac{1}{N}$, σ^2 defined in 1.7 becomes 1.1.

For convenient reference, the estimators and their variances for the five plans to be discussed are listed in Table 1.1, page 29. The variances are expressed as population values (parameters) rather than as sample estimates of variance. Each variance formula is written in a form which shows a sum of squares of deviations of points from a line (or lines). Also, an alternative

^{2/} A good reference is: Cochran, W.G., Sampling Techniques: Stratified Random Sampling, Chapter 5; Ratio Estimates, Chapter 6; Regression Estimates, Chapter 7; and for sampling with probability proportional to size see Sections 9.9, 9.10, 9.11, and 9.12 of Chapter 9.

expression for the variance of the estimator for each plan is shown. For simplicity, an assumption is made that the sampling fractions are small when the sampling is without replacement. Thus, the fpc (finite population correction) factor has been omitted from the variance formulas. The fpc, namely $\frac{N-n}{N}$, can always be included if needed. Notice in Table 1.1 that, for a constant size of sample, it is only the sums of squares that differ among the plans.

A dot chart that shows one point for each pair of values of X_i and Y_i provides simple, graphical interpretations of the sums of squares in the variance formulas for the five plans. Each variance formula for the first four plans involves the deviations of Y_i from a line through the point (\bar{X}, \bar{Y}) . The fifth plan involves line segments. How do the lines for the five plans differ and how can one judge the sampling variance for one plan compared to another by looking at a dot chart?

1.2.1 PLAN 1 - MEAN ESTIMATOR

In the first three plans, simple random sampling is assumed. These three plans differ only with regard to the method of estimating \bar{Y} . The first plan is to use the sample

average $\bar{y} = \frac{\sum y_i}{n}$ as an estimator of \bar{Y} . As a symbol for an estimator we will use \hat{y} , and a subscript will be used to distinguish the different estimators. Thus, the first estimator and its variance are

$$\hat{y}_1 = \bar{y} = \frac{\sum y_i}{n} \quad (1.8)$$

$$V(\hat{y}_1) = \frac{S_1^2}{n} = \left(\frac{1}{n}\right) \frac{\sum_{i=1}^N (Y_i - \bar{Y})^2}{N-1} \quad (1.9)$$

The formula for the variance of \hat{y}_1 contains the expression $\sum_{i=1}^N (Y_i - \bar{Y})^2$. As shown in Figure 1.1, the vertical distance between a point (X_i, Y_i) and a horizontal line through (\bar{X}, \bar{Y}) is equal to $(Y_i - \bar{Y})$. Hence $\sum_{i=1}^N (Y_i - \bar{Y})^2$ may be interpreted as the sum of squares of the deviations of Y from a horizontal line through (\bar{X}, \bar{Y}) . The closer the points are to this horizontal line, the smaller the variance of \hat{y}_1 .

In the general context of regression estimation, Plan 1 is a special case. Cochran, in Chapter 7, Sampling Techniques, discusses regression estimation where \hat{y} in the following equation is the regression estimator:

$$\hat{y} = \bar{y} + b(\bar{X} - \bar{x}) \quad (1.10)$$

The value of the regression coefficient, b , might be preassigned or it might be computed from the sample data. If it is preassigned, b is a constant when one considers the expected value of \hat{y} . If b is constant, it is clear from the theory of expected values that $E(\hat{y}) = \bar{Y}$ because the expected value of \bar{y} is \bar{Y} and the expected value of the second term, $b(\bar{X} - \bar{x})$ is zero^{3/}. Thus, the expected value of \bar{y} is \bar{Y} regardless of the value that is preassigned to b . There are cases where a preassigned value of b equal to 1 is of interest but that is not pertinent to the

^{3/} $E[b(\bar{X} - \bar{x})] = E(b\bar{X}) - E(b\bar{x}) = b\bar{X} - bE(\bar{x}) = 0$ because $E(\bar{x}) = \bar{X}$.

present discussion. The point of interest is that Plan 1 may be regarded as a special case of regression estimation where b is given a preassigned value equal to zero. In Plans 2 and 3, the value of b is computed from the sample.

1.2.2 PLAN 2 - RATIO ESTIMATOR

When we let b equal $\frac{\bar{Y}}{\bar{X}}$, the right side of Eq. 1.10

becomes $\bar{X} \frac{\bar{Y}}{\bar{X}}$ which is the estimator for Plan 2. Thus,

$$\hat{y}_2 = \bar{X} \frac{\bar{Y}}{\bar{X}} \quad (1.11)$$

This estimator is called a ratio estimator since it is the ratio of two random variables \bar{y} and \bar{x} . For simple random sampling the variance of \hat{y}_2 is often written as follows:

$$V(\hat{y}_2) = \frac{S_2^2}{n} = \left(\frac{1}{n}\right) [S_Y^2 + R^2 S_X^2 - 2RS_{XY}] \quad (1.12)$$

where

$$S_Y^2 = \frac{\sum (Y_i - \bar{Y})^2}{N-1}$$

$$S_X^2 = \frac{\sum (X_i - \bar{X})^2}{N-1}$$

$$S_{XY} = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{N-1}$$

and

$$R = \frac{\sum Y_i}{\sum X_i} = \frac{\bar{Y}}{\bar{X}}$$

The variance formula for Plan 2, Table 1.1, shows that the deviations, $(Y_i - RX_i)$, are squared and summed.

Exercise 1.2 With reference to the variance of \hat{y}_2 , Eq. 1.12, show that $S_Y^2 + R^2 S_X^2 - 2RS_{XY} = \frac{\Sigma(Y_i - RX_i)^2}{N-1}$.

Consider a line through the origin and the point (\bar{X}, \bar{Y}) , see Figure 1.1. The slope of this line is $R = \frac{\bar{Y}}{\bar{X}}$. The vertical distance between this line and a point (X_i, Y_i) is $(Y_i - RX_i)$. Therefore, the sum of squares, $\Sigma(Y_i - RX_i)^2$, in the variance formula for \hat{y}_2 is the sum of squares of the deviations of the points (X_i, Y_i) from the line through the origin and (\bar{X}, \bar{Y}) . The only difference between the variances of \hat{y}_1 and \hat{y}_2 is the difference between $\Sigma(Y_i - \bar{Y})^2$ and $\Sigma(Y_i - RX_i)^2$. The points for the assumed population in Figure 1.1 are somewhat closer to the line through the origin and (\bar{X}, \bar{Y}) than to a horizontal line through (\bar{X}, \bar{Y}) . Therefore, one would expect \hat{y}_2 to have a smaller sampling variance than \hat{y}_1 .

Exercise 1.3 Verify that $Y_i - RX_i$ is the vertical distance between a point (X_i, Y_i) and a straight line that passes through the origin and (\bar{X}, \bar{Y}) .

1.2.3 PLAN 3 - REGRESSION ESTIMATOR

The estimator, \hat{y}_3 , in Plan 3 is called a regression estimator. It makes use of a line that is derived by applying the least squares method in fitting a line to the sample values of x and y . The equation for the least squares line (fitted to

the sample data) may be written as follows:

$$\hat{y}_i = \bar{y} + b(x_i - \bar{x}) \quad (1.13)$$

where
$$b = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}, \quad i = 1, \dots, n$$

and \hat{y}_i is the point on the line where x is equal to x_i . The estimator of \bar{Y} is obtained by substituting \bar{X} for x_i in 1.13 which gives

$$\hat{y}_3 = \bar{y} + b(\bar{X} - \bar{x}) \quad (1.14)$$

To understand the variance formula for \hat{y}_3 , suppose a least squares line is determined for the population of points shown in Figure 1.1. It is

$$\hat{Y}_i = \bar{Y} + B(X_i - \bar{X}) \quad (1.15)$$

where
$$B = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2}, \quad i = 1, \dots, N.$$

and \hat{Y}_i is the point on the line where X is equal to X_i . This line has been determined so the sum of the squares of the deviations of Y_i from it is a minimum. That is, $\sum_{i=1}^N (Y_i - \hat{Y}_i)^2$ is less than the sum of the squares of the deviations from any other straight line. The sum of squares of the deviations of Y_i from the least-squares regression line can be written as follows:

$$\sum_{i=1}^N (Y_i - \hat{Y}_i)^2 = \sum_{i=1}^N \{Y_i - [\bar{Y} + B(X_i - \bar{X})]\}^2 \quad (1.16)$$

The expression on the right side of 1.16 appears in the variance formula for \hat{y}_3 in Table 1.1 which is

$$V(\hat{y}_3) = \frac{S_3^2}{n} = \left(\frac{1}{n}\right) \frac{\sum \{Y_i - [\bar{Y} + B(X_i - \bar{X})]\}^2}{N-1} \quad (1.17)$$

Exercise 1.4 Show that the right side of 1.16 reduces to $(1-r^2)\sum(Y_i - \bar{Y})^2$ where r is the coefficient of correlation between X and Y .

1.2.4 DISCUSSION OF PLANS 1, 2, and 3

The variances of \hat{y}_1 , \hat{y}_2 , and \hat{y}_3 have been related to the sums of squares of deviations from three lines respectively:

(1) a horizontal line through (\bar{X}, \bar{Y}) , (2) a ratio line (that is, a line through the origin and (\bar{X}, \bar{Y}) , and (3) a regression line (which is a line determined by the method of least squares).

Since the sum of squares of deviations from the regression line is least, the variance of \hat{y}_3 will generally be less than the variances for \hat{y}_1 and \hat{y}_2 . The comparative variances can be judged from visual examination of how close the points are to each of the three lines.

The variance of \hat{y}_2 is not always less than the variance of \hat{y}_1 . Moreover, the correlation coefficient is not a reliable measure of how the variances of \hat{y}_1 and \hat{y}_2 compare. According to Eq. 1.12, $2RS_{XY}$ must be larger than $R^2 S_X^2$ or the variance of \hat{y}_2 will be larger than the variance of \hat{y}_1 . In other words, use of an auxiliary variable in a ratio estimator could result in an increase rather than a decrease in variance.

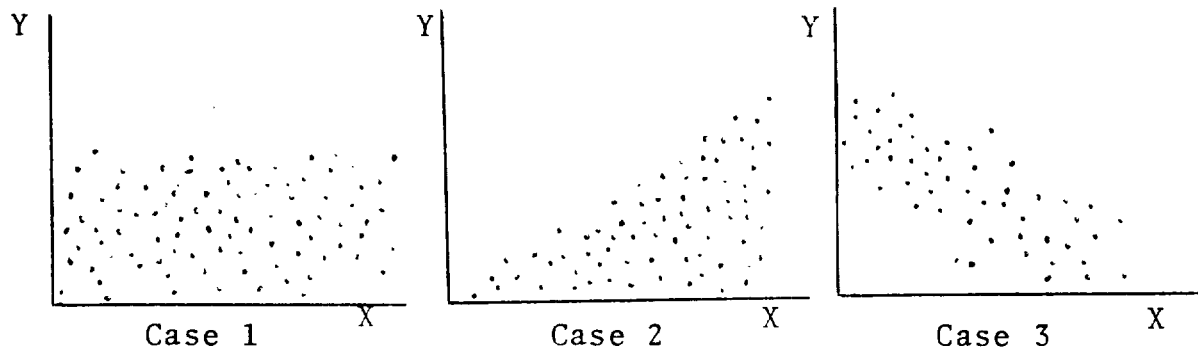
The variance formulas discussed above are population variances (parameters) which must be estimated from the sample. For all three plans, formula for estimating the sampling variances are of the same format as the population variance formula. The only difference is that the sum of squares is computed from sample data instead of data for the entire population. The variance formulas for Plans 2 and 3 are large sample approximations, which are commonly used in practice. (See Cochran's book sections 6.4 and 7.4.)

In a survey involving many variables and tabulations by various classifications, the first two estimators (plans) are commonly used. Although the variance of \hat{y}_3 is, to some degree, generally less than the variance of \hat{y}_1 or \hat{y}_2 , its use is generally limited to special situations where low error is very important and the variance of \hat{y}_3 is appreciably less than the variance of \hat{y}_1 or \hat{y}_2 . For example, it might be used to estimate the production of a particular commodity or when it is very important to make estimates with a high degree of accuracy for a few selected characteristics.

All three of the estimators may be used with sampling plans other than simple random sampling; for example, ratio estimators and stratified random sampling are quite common.

Exercise 1.5 For the special case where the regression line is the same as the ratio line, show that the variance of \hat{y}_3 is equal to the variance of \hat{y}_2 . Can $V(\hat{y}_3)$ ever be larger than $V(\hat{y}_2)$?

Exercise 1.6 Compare Plans 1, 2, and 3 with regard to the following three dot charts representing three different relations between X and Y.



For each of the three cases rank the three plans from largest to smallest sampling variance.

1.2.5 PLAN 4 - SAMPLING WITH PPS

Plans 2 and 3 used the auxiliary variable in estimation and not in the design or selection of a sample. Plan 4 is to select a sample of n elements with replacement and to use probabilities of selection proportional to X_i . By substituting $\frac{x_i}{\bar{X}}$ for p_i in Eq. 1.5 and $\frac{X_i}{\bar{X}}$ for P_i in 1.7, the following expressions are obtained for the estimator and its variance:

$$\hat{y}_4 = \bar{X} \left(\frac{1}{n} \right) \sum \frac{y_i}{x_i} \quad (1.18)$$

and

$$V(\hat{y}_4) = \frac{\sigma_4^2}{n} = \left(\frac{1}{n} \right) \left(\frac{1}{N} \right) \sum \left(\frac{\bar{X}}{X_i} \right) (Y_i - RX_i)^2 \quad (1.19)$$

The formula for the variance of \hat{y}_4 shows that $(Y_i - RX_i)$ are the deviations which are squared. Thus, the line involved

in Plan 4 is the same as the line for the ratio estimator. Notice that the squares of the deviations, $(Y_i - RX_i)^2$, are weighted by $\frac{1}{X_i}$ owing to the unequal probability of selection. For the ratio estimator, the squares of the deviations were weighted equally. Incidentally, the appropriate formula for estimating the variance of \hat{y}_4 from sample data is not of the same form (and will not reduce to the same form) as Eq. 1.19.

In practice one often finds that the variance of the deviations, $(Y_i - RX_i)$, increases as X increases. That is, the values of Y are usually more widely scattered for large values of X than for small values of X. If the relation between X and Y is like the dot chart in Figure 1.2, Plan 4 will have a lower sampling variance than the first three plans. A line through (\bar{X}, \bar{Y}) and the origin fits the data about as well as any line. But, \hat{y}_4 would have the least sampling variance because, as shown in the formula for its variance, the largest values of $(Y_i - RX_i)^2$ receive the smallest weights in the sum of squares. Judging the effectiveness of Plan 4 is more than a matter of observing how well the data fit a line through (\bar{X}, \bar{Y}) and the origin. In fact, it is easy to misjudge the effectiveness of sampling with pps. We will return to this point after presentation of Plan 5.

Exercise 1.7 Start with σ^2 as defined in 1.7 and show that it reduces to $(\frac{1}{N}) \sum \frac{\bar{X}}{X_i} (Y_i - RX_i)^2$ when $P_i = \frac{X_i}{\bar{X}}$ and $R = \frac{Y}{\bar{X}}$.

1.2.6 PLAN 5 - STRATIFIED SAMPLING

This plan makes use of the variable X as a basis for stratification. Suppose the sampling units in the population

have been listed in order from smallest to largest values of X.

The list is then divided into L strata. Let

N_h = the population number of su's in stratum h,

n_h = the sample number of su's,

$f_h = \frac{n_h}{N_h}$ = the sampling fraction,

Y_{hi} and X_{hi} = the values of Y and X for the i^{th} su in stratum h,

S_{Yh}^2 = the variance of Y within stratum h,

\bar{Y}_h = the average value of Y in stratum h, and

\bar{X}_h = the average value of X in stratum h.

We are primarily interested in proportional allocation of the sample to strata for comparison with Plans 1, 2, and 3, and in optimum allocation for comparison with Plan 4.

With proportional allocation the sampling fractions, f_h , are all equal and it is appropriate to use the unweighted sample mean as an estimator of \bar{Y} . Hence,

$$\hat{y}_5 = \bar{y} \quad (1.20)$$

Assuming simple random sampling within strata and that the fpc's are negligible,

$$V(\hat{y}_5) = \frac{S_5^2}{n} \quad (1.21)$$

where

$$S_5^2 = \frac{1}{N} \sum N_h S_{Yh}^2$$

and

$$S_{Yh}^2 = \frac{\sum_i (Y_{hi} - \bar{Y}_h)^2}{N_h - 1}$$

With reference to a dot chart for showing deviations that are squared in the variance formulas, instead of one line, we now have a series of line segments, one for each stratum, as shown in Figure 1.3. Each line segment is a horizontal line through the stratum mean. The sampling variance, $S_{\bar{y}}^2$, is an average of the squares of deviations from these horizontal line segments. If the points are close to the line segments, the sampling variance will be small for stratified random sampling.

Consider what happens to the sum of squares for stratified random sampling as the number of strata increases, that is, as the difference between the largest and smallest value of X for each stratum decreases. If the relation between X and Y over the whole population is approximately linear, the sum of squares of the deviations from the line segments will become approximately equal to the sum of squares of the deviation from a regression line as in Plan 3. Under those conditions Plans 3 and 5 would have approximately the same sampling variance. If the relation between X and Y is not linear, the sampling variance for Plan 5 might be less than the sampling variance for Plan 3, depending on the width of the stratum intervals, the degree of nonlinearity, and how close the points are to a curved line.

Suppose the ratio line (that is, a straight line through (\bar{X}, \bar{Y}) and the origin) fits the points about as well as any line. In this case, the sampling variances for Plans 2, 3 and 5 (assuming the stratum intervals are small) would be approximately equal.

Plan 4 must be judged with regard to how well the probabilities of selection fit the situation as well as the closeness of the points to the ratio line. It is helpful to compare it with using the auxiliary variable for stratification and optimum allocation of the sample to strata. We know that the optimum size of sample from stratum h is proportional to $N_h S_{Yh}$. Or, in terms of sampling fractions, the optimum sampling fraction, f'_h , is proportional to S_{Yh} .

In stratified sampling, the optimum sampling fractions are proportional to \bar{X}_h when S_{Yh} is proportional to \bar{X}_h . In this case, the selection probabilities in sampling with pps would be approximately in proportion to \bar{X}_h provided the stratum intervals are small. In other words, when S_{Yh} is proportional to \bar{X}_h the optimum sampling fractions in stratified sampling are in close agreement with the selection probabilities in sampling with pps. It is very important to recognize that the situation most favorable for sampling with pps occurs when (1) the data follow the ratio line, and (2) the conditional standard deviation of Y is proportional to X . ("Conditional standard deviation" refers to the standard deviation of Y for a given value of X .) The dot chart, Figure 1.2, meets those conditions. Notice that the vertical distance between the two dotted lines is proportional to X ; hence, the conditional standard deviation of Y is, at least roughly, proportional to X .

Recognition of a relation like the one in Figure 1.2 as a good case for sampling with pps provides guidance when making a

choice among alternatives including the possibility of making a transformation of X that would provide a better measure of size. Sometimes a simple transformation like $X'_i = X_i + C$, where C is a constant, will provide a measure of size, X' , such that the conditional standard deviation of Y will be in proportion to X' . In some cases, a simple transformation can change sampling with pps, compared to Plan 1, from a substantial increase in sampling variance to an important reduction. With pps sampling it is important that the maximum values of Y approach zero as X approaches zero.

One might feel that sampling with probability proportional to X does not fully remove, from the sampling variance, variation among strata when X is the criterion for stratification. Look at the pps estimator. It is variation in the stratum ratios,

$$R_h = \frac{1}{N_h} \sum_i \frac{Y_{hi}}{X_{hi}} \text{ rather than variation in } \bar{Y}_h \text{ that needs to be}$$

considered. It will be easier to discuss this point in the next chapter when stratification in combination with different methods of estimation is considered.

Some numerical results as well as dot charts will be presented later in this chapter and in Chapter II.

Exercise 1.8 Refer to Figure 1.2 and verify from theorems pertaining to similar triangles that the range in values of Y is proportional to X . In this case, as a rough approximation, we may regard the standard deviation of Y as being in proportion to X . Is it possible in sampling with probability proportional

to X to have a lower sampling variance than sampling with stratification by X and optimum allocation? When?

Exercise 1.9 (a) Refer to Figure 1.1 and rank Plans 1, 2, 3, and 5 from least variance to highest. Ans. 3, 5, 2, 1 with 3 and 5 being close depending on the number of strata.

(b) It appears that the variance for Plan 4 would be much larger than the variance for stratified random sampling with optimum allocation. Why? Look at the conditional standard deviation of Y .

(c) Since the range in the optimum sampling fractions for stratified random sampling is small, would you agree that Plan 4 would have a much larger variance than Plan 1?

(d) Consider the simple transformation $X'_i = X_i + C$ where C is a constant. Is there a value of C such that X' would be an effective measure of size.

Exercise 1.10 Refer to Exercise 1.6 and for each case rank all five plans with regard to sampling variance.

Exercise 1.11 Prepare a dot chart showing a relation between X and Y such that stratified random sampling with allocation proportional to N_h , Plan 5, will have a smaller sampling variance than the regression estimator, Plan 3.

Exercise 1.12 Prepare a dot chart such that the variance for Plan 5 with proportional allocation will be approximately equal to the variance for Plan 1 and (at the same time) the variance for Plan 5, with optimum allocation will be much

less than the variance for Plan 1. This would be a case where gain from stratification would be entirely attributable to varying sampling fractions rather than stratification to remove variation associated with differences among stratum means.

1.2.7 SUMMARY

If there is no relation between X and Y, including a relation between X and the conditional standard deviation of Y, information about X offers no possibilities for reducing sampling variance; in fact, the sampling variance could be increased by using X. If there is a relation, some alternative ways to take advantage of it have been shown. Clearly, the most effective way of using an auxiliary variable depends on what the relation is like.

In the sampling and estimation specifications for a particular survey, an auxiliary variable would generally be used in only one way. For example, attempting to use a relationship between X and Y as a basis for stratification and also in estimation is generally not advisable. Try to fully utilize the potential contribution of an auxiliary variable in one way. Whether an auxiliary variable is used in stratification or in estimation might depend on the nature of other auxiliary variables that are available. For example, some kinds of auxiliary variables are readily useful in stratification but not estimation. Consider using quantitative measures in estimation or in sampling with pps and using nonquantitative measures in stratification. This point will receive further attention.

1.3 NUMERICAL EXAMPLE

Although our interest is in the practical application of sampling theory, a major objective in the presentation of numerical illustrations in this and later chapters is to improve one's comprehension of patterns of variation that exist and to develop one's skill at judging the effectiveness of alternative sampling and estimation methods in specific situations. It is informative to apply several alternatives to the same population even though some of the alternatives are not practically feasible.

The data for the following example were taken from a research project to develop techniques for sampling apple trees to forecast and estimate apple production. The primary purpose was to make an intensive investigation of ways of sampling a tree rather than how to select a sample of trees. As a part of this project, the branches on six apple trees were mapped. Included among the measurements that were taken are the cross-sectional area of each branch and the number of apples on each branch. There was a total of 28 primary branches on the six trees. A primary branch, which is a branch from the tree trunk, probably would not be used as a sampling unit in practice. However, data for these 28 primary branches are useful as a numerical example of alternative ways of using an auxiliary variable. Also the results will be useful in later discussions and comparisons of methods of sampling within trees.

For purposes of this numerical example, the 28 primary branches is the population of sampling units. We assume the purpose of sampling is to estimate the total number of apples on the six trees. The auxiliary variable X is the csa (cross-sectional area) of a branch. The fruit counts, Y , and the csa's, X , for the 28 limbs are presented in Table 1.2. Let us compare the five plans outlined above by referring to a dot chart. Figure 1.4 shows the points (X_i, Y_i) and three lines: (1) the horizontal line for Plan 1, (2) a ratio line through the origin and (\bar{X}, \bar{Y}) which pertains to Plans 2 and 4, and (3) the least squares regression line for Plan 3. To order the sampling variances from smallest to largest, one would undoubtedly rank the first three plans in the order 3, 2, and 1, with 1 having a much larger variance than the other two. Since the scatter of the points increases as the csa increases, one might expect Plan 4 to be better than Plan 2, but Plan 4 is somewhat difficult to judge. In Chapter II, similar comparisons of the plans will be made using terminal branches (and hence more points) as sampling units.

The total number of sampling units, 28, is too small to provide a good example of stratified random sampling in comparison to the other four plans. However, for purposes of illustration, a comparison will be made. Since 28 is divisible by 4, it is convenient to divide the branches, after being ordered by csa, into four strata of 7 branches each as presented in Table 1.2.

The stratum boundaries are indicated by vertical dotted lines in Figure 1.4. It is evident that line segments, for the stratified random sampling as specified in the preceding paragraph, do not fit the data as well as the regression line, Plan 3. Although the sampling variance for Plan 5 is clearly much less than the variance for Plan 1, it is undoubtedly greater than the variance for Plan 3. Its rank compared to Plans 2 and 4 is uncertain.

We will now compare the judgments formed from looking at Figure 1.4 with numerical results. The relative variances of the five estimators, assuming $n = 1$ (that is, a sample of one branch), are presented in Table 1.3. Relative variances are the variances divided by \bar{Y}^2 . Although it is not possible to select a stratified random sample of one branch, it is appropriate to let $n = 1$ for purposes of comparing Plan 5 with the other plans.

In this example, the relationship between X and Y is such that all four Plans 2, 3, 4, and 5 provide large reductions in sampling variance. Stratification, as applied, reduced the sampling variance by more than 80 percent compared to Plan 1 but not as much as Plans 2, 3, and 4 because it did not utilize as fully the information provided by X . If it were feasible to divide the population into more strata, perhaps 8 or 10 instead of 4, the relative variance for Plan 5 would have been less than 0.307 and perhaps nearly as low as the variance for the regression estimator, Plan 3. However, from the results that we have seen, it appears that the auxiliary variable X can be used to reduce

the sampling variance from 1.117 to about 0.200. Some of the practical considerations in the choice of a plan will be discussed later. In the next section our understanding of sampling with pps will be extended by comparing it to stratification with optimum allocation.

1.3.1 VARYING THE SAMPLING FRACTION WITH SIZE OF SAMPLING UNIT

From Figure 1.4 it is clear that the variance of the number of apples increases with the size of branch. The standard deviation within strata and the average csa per branch are presented in Table 1.4.

Since the largest S_{Yh} is about 10 times larger than the smallest, the largest sampling fraction (with stratified sampling and optimum allocation) would be about 10 times larger than the smallest. This range of variation in sampling fractions is large enough to expect optimum allocation, compared to proportional, to give a substantial reduction in variance. The relative variance for optimum is 0.211 compared to 0.301 for proportional.

With reference to sampling with pps, notice that the conditional standard deviation of Y is roughly in proportion to X . This is indicated by the fact that the ratio of S_{Yh} to \bar{X}_h , Table 1.4, is nearly constant. Also, the points in Figure 1.4 follow, approximately, a line through the origin and (\bar{X}, \bar{Y}) . Therefore, it is reasonable to find that 0.211, the variance for stratified sampling with optimum allocation, is close to 0.194, the variance for sampling with pps.

Since S_{Y_h} is approximately in proportion to \bar{X}_h , csa is a good measure of size. However, it is informative to compare the five plans when circumference is used or a measure of size of branch. To examine the relation between number of apples and circumference, see Figure 1.5. Notice that the least squares line (Plan 3) departs farther from the origin than did the least squares line for csa , Figure 1.4. This is reflected in the variances which are presented in Table 1.5. The relative variance, 0.256, for Plan 3 is considerably less than the relative variances for Plans 2 and 4. Also notice that circumference is less effective than csa for all three Plans 2, 3, and 4.

Exercise 1.13 Refer to Table 1.2 and compute the four values of \bar{X}_h taking the circumference as the auxiliary variable. Compare these values of \bar{X}_h with the values of S_{Y_h} given in Table 1.4. What does this comparison indicate regarding the use of circumference as a measure of size in pps sampling?

Notice that csa is a mathematical transformation of circumference. The question might be asked, "Is there a better transformation?" This question will be given further attention in the next chapter. For the research study, a csa measurement was made by wrapping a tape around the base of a branch. The tapes had been calibrated to give a direct reading of the csa assuming the branch is circular. Figure 1.4 suggests that csa is a good measure of size for sampling with pps, but broader experience is needed. In a later illustration it will become evident that sampling with pps is a good practical method of selecting a sample of branches.

Exercise 1.14 By careful planning one can compute sub-

totals and totals of ΣY_i , ΣX_i , ΣY_i^2 , $\Sigma X_i Y_i$, and $\Sigma \frac{Y_i^2}{X_i}$ that provide intermediate results from which the variances for several alternative plans are easily obtained. For purposes of computation show that the values of S^2 for the five plans may be written as follows:

$$S_1^2 = \left(\frac{1}{N-1}\right) \left[\Sigma Y_i^2 - \frac{(\Sigma Y_i)^2}{N}\right]$$

$$S_2^2 = \left(\frac{1}{N-1}\right) \left[\Sigma Y_i^2 - 2R \Sigma X_i Y_i + R^2 \Sigma X_i^2\right] \text{ where } R = \frac{\Sigma Y_i}{\Sigma X_i}$$

$$S_3^2 = S_1^2 (1-r^2) \text{ where } r \text{ is the correlation coefficient}$$

$$\sigma_4^2 = \left(\frac{\bar{X}}{N}\right) \Sigma \frac{Y_i^2}{X_i} - \bar{Y}^2$$

Since there are 7 branches in each stratum the expression in Table 1.1 for S_5^2 reduces to

$$S_5^2 = \left(\frac{1}{N-4}\right) \left[\Sigma Y_i^2 - \frac{\Sigma Y_h^2}{7}\right] \text{ where } Y_h \text{ is the total of } Y \text{ for stratum } h.$$

From Table 1.2 the following intermediate results are obtained:

$\Sigma Y_i = 7,199$	$\Sigma X_i = 157.76$
$\Sigma Y_i^2 = 3,844,283$	$\Sigma X_i^2 = 1,329.98$
$\Sigma X_i Y_i = 67,633.47$	$\Sigma \frac{Y_i^2}{X_i} = 392,247.3$

The stratum totals, Y_h , are

$$Y_1 = 202, Y_2 = 923, Y_3 = 1,594, \text{ and } Y_4 = 4,480$$

Compute the values of S_1^2 , S_2^2 , S_3^2 , σ_4^2 , and S_5^2 .

Answer: $S_1^2 = 73,828$

$$S_2^2 = 16,339$$

$$S_3^2 = 12,292$$

$$\sigma_4^2 = 12,826$$

$$S_5^2 = 20,274$$

Table 1.1--Estimators and Their Relative Variances 1/

Plan	Estimator	Variance of estimator	S ² or σ ² expressed as an average of squared deviations	An alternative expression for S ² or σ ²
1	$\hat{y}_1 = \bar{y}$	$(\frac{1}{n})S^2$	$S^2_1 = \frac{\Sigma(Y_i - \bar{Y})^2}{N-1}$	$S^2_1 = S^2_Y$
2	$\hat{y}_2 = \bar{X} \frac{\bar{Y}}{\bar{X}}$	$(\frac{1}{n})S^2$	$S^2_2 = \frac{\Sigma(Y_i - RX_i)^2}{N-1}$	$S^2_2 = S^2_Y + R^2 S^2_X - 2RS_{XY}$
3	$\hat{y}_3 = \bar{y} + b(\bar{X} - \bar{x})$	$(\frac{1}{n})S^2_3$	$S^2_3 = \frac{\Sigma\{Y_i - [\bar{Y} + B(X_i - \bar{X})]\}^2}{N-1}$	$S^2_3 = S^2_Y(1-r^2)$
4	$\hat{y}_4 = \bar{X}(\frac{1}{n})\Sigma \frac{Y_i}{X_i}$	$(\frac{1}{n})\sigma^2$	$\sigma^2_4 = \frac{\Sigma(\frac{\bar{X}}{X_i})(Y_i - RX_i)^2}{N}$	$\sigma^2_4 = \frac{1}{N^2} \Sigma P_i (\frac{Y_i}{P_i} - Y)^2$
29	$\hat{y}_5 = \frac{\Sigma N_h \bar{y}_h}{N} = \bar{y}$	$(\frac{1}{n})S^2_5$	$S^2_5 = \frac{1}{N} \Sigma N_h \frac{\Sigma (Y_{hi} - \bar{Y}_h)^2}{N_h - 1}$	$S^2_5 = \frac{1}{N} \Sigma N_h S^2_h$

1/ Upper case letters refer to population values, lower case to sample values.

N = total number of units in population.
n = total number of units in sample.
L = number of strata.
N_h = number of units in the population in stratum h.
 $N = \Sigma N_h$
n_h = number of units in sample from stratum h.
 $n = \Sigma n_h$
 $Y = \Sigma Y_i$

$\bar{Y} = \frac{\Sigma Y_i}{N}$	Y_{hi} = value of Y for the i th unit in stratum h.	$r = \frac{S_{XY}}{(S_Y)(S_X)}$
$X = \frac{\Sigma X_i}{N}$	$\bar{Y}_h = \frac{\Sigma Y_{hi}}{N_h}$ = mean of Y in stratum h.	$B = \frac{S_{XY}}{S^2_X}$
$\bar{X} = \frac{\Sigma X_i}{N}$	$S^2_Y = \frac{\Sigma (Y_i - \bar{Y})^2}{N-1}$	$b = \frac{S_{XY}}{S^2_X}$
$P_i = \frac{X_i}{X}$	$S^2_X = \frac{\Sigma (X_i - \bar{X})^2}{N-1}$	$S^2_h = \frac{\Sigma (Y_{hi} - \bar{Y}_h)^2}{N_h - 1}$
$R = \frac{\bar{Y}}{\bar{X}}$	$S_{XY} = \frac{\Sigma (Y_i - \bar{Y})(X_i - \bar{X})}{N-1}$	

Table 1.2--Data for Primary Branches on Six Apple Trees

(Arrayed by csa)

Stratum	Branch ^{1/}	csa ^{2/}	Cir. ^{3/}	No. of apples	Stratum	Branch ^{1/}	csa ^{2/}	Cir. ^{3/}	No. of apples
1	1-4	.87	3.3	5	3	6-3	4.84	7.8	183
	1-5	1.03	3.6	34		1-2	5.09	8.0	40
	5-6	1.34	4.1	4		2-4	5.75	8.5	396
	1-3	1.83	4.8	59		6-2	5.89	8.6	250
	5-4	1.83	4.8	18		2-3	6.16	8.8	157
	5-5	1.83	4.8	17		5-1	6.16	8.8	179
	6-4	1.99	5.0	65		4-2	7.18	9.5	389
2	2-5	2.68	5.8	89	4	2-2	8.94	10.6	333
	4-4	2.86	6.0	238		4-1	9.28	10.8	696
	4-5	2.86	6.0	81		2-1	9.63	11.0	473
	4-3	3.57	6.7	254		3-1	11.60	12.1	762
	1-1	3.68	6.8	76		3-3	12.84	12.7	517
	5-3	4.48	7.5	97		3-2	13.45	13.0	622
	5-2	4.72	7.7	88		6-1	15.38	13.9	1,077
					TOTAL		157.76	221.0	7,199

- 1/ Tree (first digit) and branch within a tree (second digit).
 2/ Cross-sectional area of branch in square inches.
 3/ Circumference of branch in inches.

Table 1.3--Relative Variances of Estimators

Plan	Relative variance of \hat{y}
1	1.117
2	0.247
3	0.186
4	0.194
5	0.307

Table 1.4--Mean csa and Standard Deviation of Y by Strata

Stratum	Mean csa, \bar{x}_h	Standard Deviation, S_{Yh}	$\frac{S_{Yh}}{\bar{x}_h}$
1	1.53	24.8	16.2
2	3.55	78.4	22.1
3	5.87	129	22.0
4	11.59	240	20.7

Table 1.5--Relative Variances When the Auxiliary Variable is Circumference

Plan	Relative variance of \hat{y}
1	1.117
2	0.559
3	0.256
4	0.438

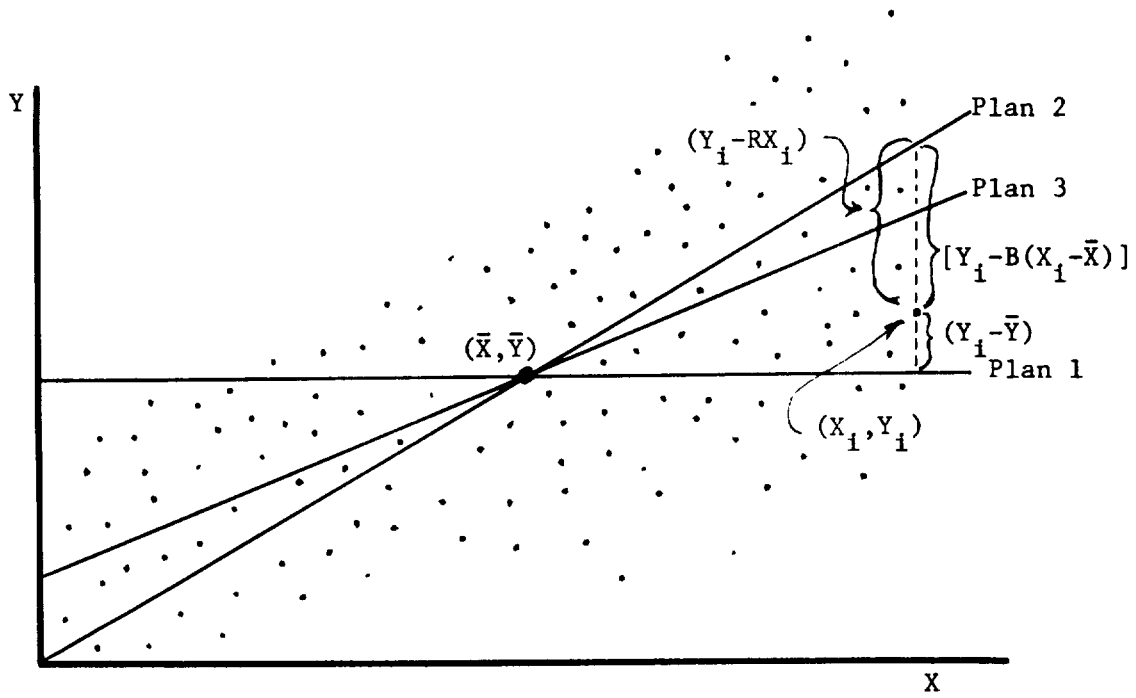


Figure 1.1--Deviations in Variance Formulas for Plans 1, 2, and 3

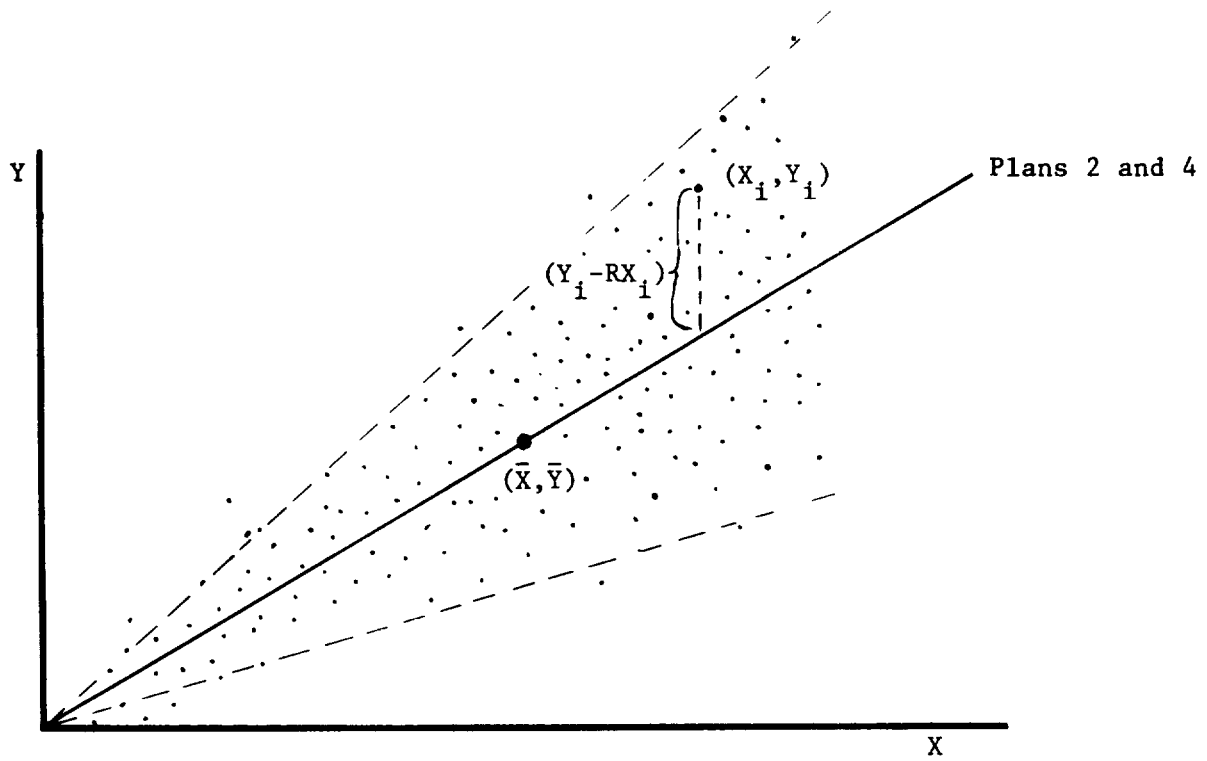


Figure 1.2--Deviations in Variance Formulas for Plans 2 and 4

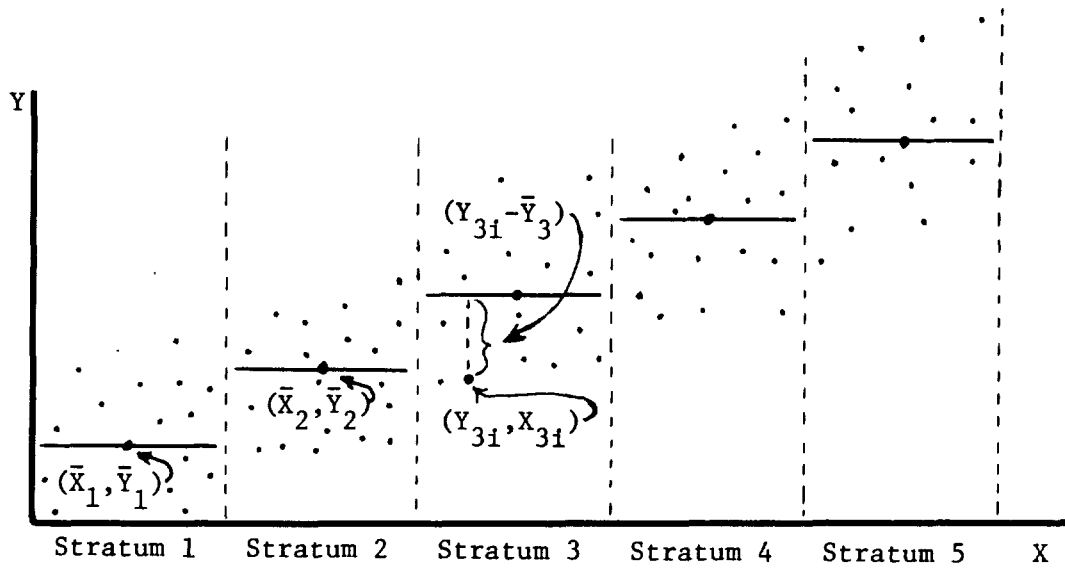


Figure 1.3--Deviations in Variance Formula
for Plan 5, Stratified Random Sampling

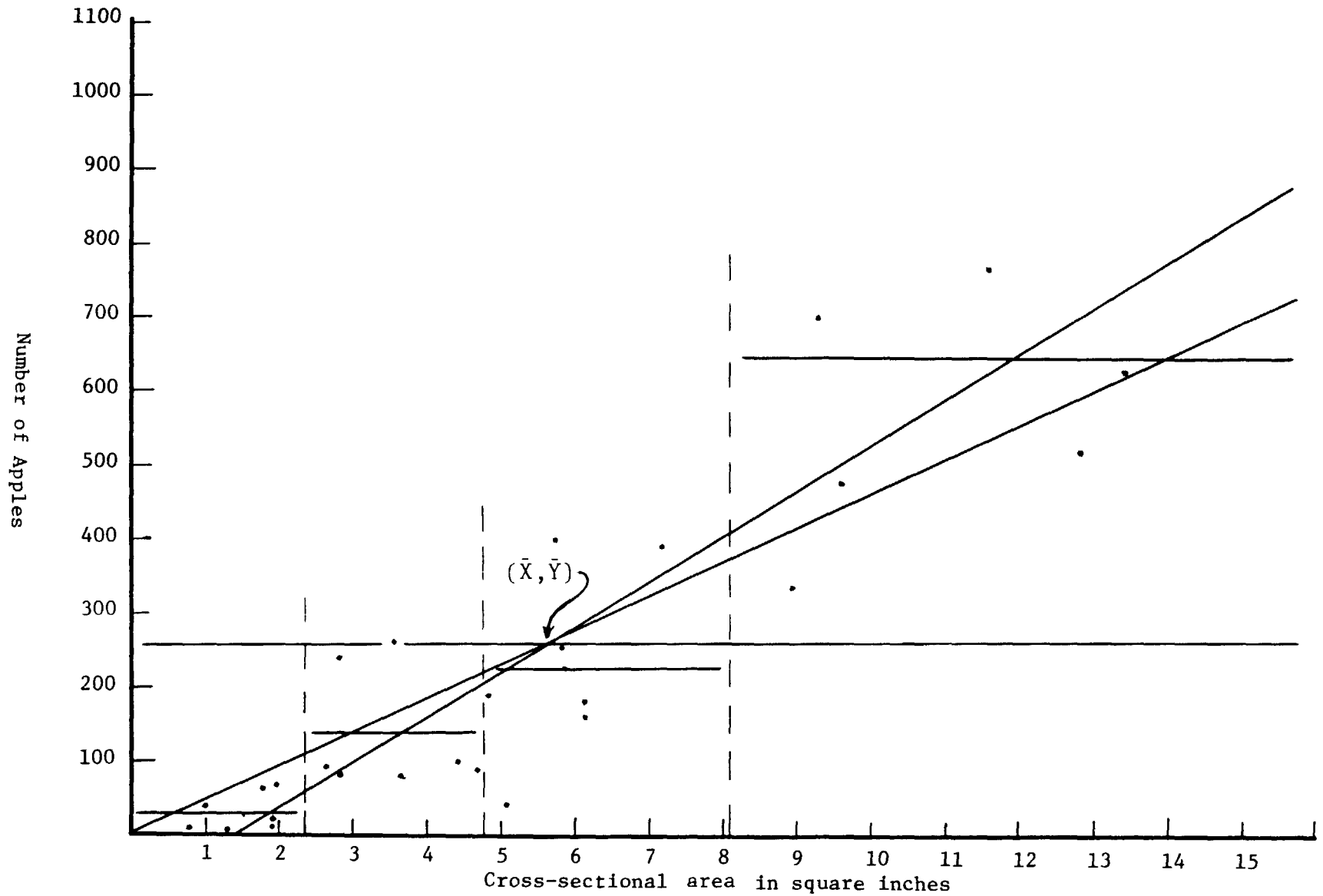


Figure 1.4--Relation between Number of Apples and CSA

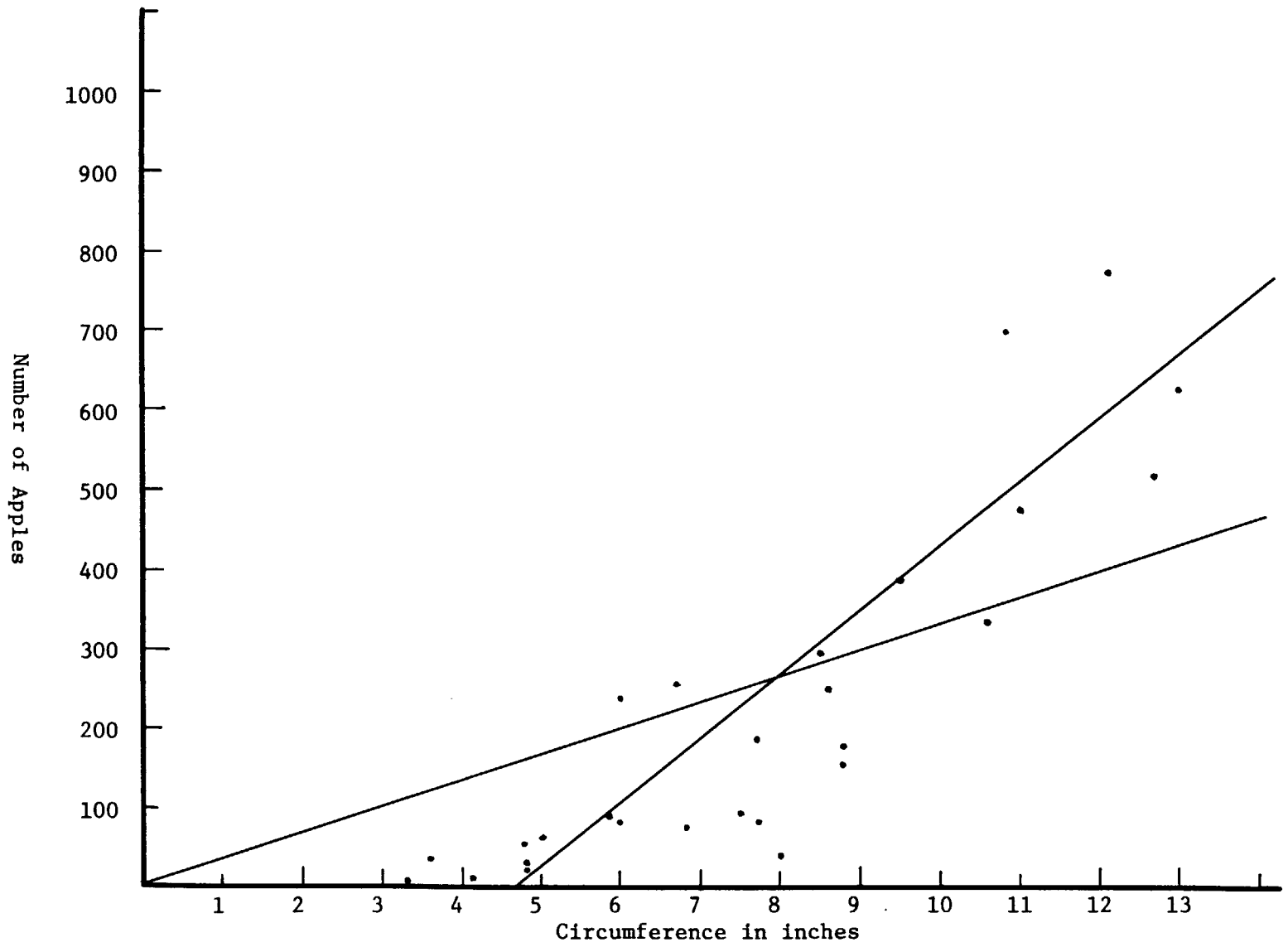


Figure 1.5--Relation between Number of Apples and Circumference

CHAPTER II

FURTHER OBSERVATIONS ON USES OF AN AUXILIARY VARIABLE

2.1 INTRODUCTION

The effects on sampling variance of various factors in sample design and estimation are not independent. For example, the difference in the sampling variance between a mean estimator and a ratio estimator might vary with the definition of the sampling unit or with the criteria used for stratification. In this chapter some numerical examples that display such interactions will be given. The objective is to further develop a perception of patterns (or components) of variation and ability to judge how alternative methods rank with regard to sampling variance. As you study and acquire experience in sampling try to visualize the pattern of variation in a population to be sampled and test your skill at prejudging the effectiveness of alternative sampling plans.

The data for the examples in this chapter are taken from the research project on methods of estimating apple production which was referred to in Chapter I. The sampling alternatives that are considered require a map of each tree that is sampled. That is, a map of a tree which defines the sampling units (branches) is the sampling frame. Methods of probability sampling are available which do not require preparing a complete map of a tree. This will be discussed in Chapter III.

As background, refer to Figure 2.1 which is a map of one of the six apple trees used for the numerical example presented in Chapter I. The map shows the scheme that was used for identifying branches. For example, 3-1-4 refers to third-stage branch number 4 from second-stage branch number 1 and first-stage branch number 3. Branches from the tree trunk were mapped until "terminal" branches were reached. "Terminal branch" refers to the last stage of branching where the mapping of branches was terminated. The csa's (cross sectional areas) of the terminal branches ranged from about 3/4 to 2 square inches which seemed to be about the smallest practical size of branch to consider as a sampling unit. There were 28 primary branches and 135 terminal branches on the six trees. The average number of apples on a terminal branch was about 50.

When following a tree trunk to primary branches, to second-stage branches, etc., small branches are sometimes found which are not large enough to be classified as terminal branches. For example, six apples were found on small branches on primary branch number 2 before the 4 second-stage branches 2-1, 2-2, 2-3, and 2-4 were reached. Apples on such branches have been called "path" fruit, meaning fruit on the path of a terminal branch. Path fruit present some special problems which will be discussed in Chapter III. The amount of path fruit is relatively small and will be ignored in this chapter.

For each of the first four plans that were discussed in Chapter I primary and terminal branches will be compared as

sampling units. Then, using terminal branches, the first four plans will then be applied within strata (trees) for comparison with each of the four plans when there is no stratification.

2.2 COMPARISON OF PRIMARY AND TERMINAL BRANCHES AS SAMPLING UNITS

The number of apples on each of the 28 primary branches and the csa of each branch were presented in Table 1.2. Data for the 135 terminal branches are presented in Table 2.1. The number of apples on primary branches included path fruit whereas the numbers on terminal branches do not. The difference is presumed to be negligible for purposes of an exercise in variance comparisons. Figures 1.4 and 2.2 are the dot charts for primary and terminal limbs respectively.

Table 2.2 presents relative variances for terminal and primary branches. The relative variances for primary branches are taken from Table 1.3 in Chapter I, and relative variances for terminal branches were computed using the same variance formulas.

When interpreting variances it is essential that the dimensions of the variances be clear. What variation does a particular variance measure and in what units is the variance expressed? Are the relative variances in Table 2.2 comparable? Let us examine the formula for the relative variance (RV) of \hat{y}_1 , which is

$$\text{RelVar } (\hat{y}_1) = \frac{1}{\bar{y}^2} \left(\frac{1}{n} \right) (S_1^2) \quad (2.1)$$

where
$$S_1^2 = \frac{\Sigma (Y_i - \bar{Y})^2}{N-1}$$

A quantity like S_1^2 is sometimes called "unit variance" as it is a measure of variation among individual sampling units. The quantity $\frac{S_1^2}{\bar{Y}_1^2}$ may be called "unit-relative variance" which is the square of the coefficient of variation among individual units. In Eq. 2.1, when $n = 1$ the relative variance of \hat{y}_1 , is the unit-relative variance. A similar interpretation of the variance formula for the other estimators holds. Thus, S_2^2 is the unit variance that pertains to the ratio estimator, \hat{y}_2 .

The variances presented in Table 2.2 are unit-relative variances which may be regarded as sampling variances for samples of one branch. Usually sampling variances for alternative plans are compared under one of two conditions: equal sampling fractions or equal costs. In this chapter the comparisons will be under an assumption of equal sampling fractions. The sampling fractions are $\frac{1}{28}$ and $\frac{1}{135}$, respectively, for one primary branch and one terminal branch.

To achieve comparability, the variances for primary branches will be converted to the equivalent of one terminal branch. That is, we want to find the variances for primary branches that correspond to a sampling fraction of $\frac{1}{135}$. There is an average of $\frac{135}{28} = 4.82$ terminal branches per primary branch.

Ignoring the fpc (finite population correction), the relative variance of the first estimator, \hat{y}_1 , is $\frac{1.17}{n'}$ for a sample of n' primary branches and is $\frac{0.660}{n}$ for a sample of n terminal branches. (The numbers, 1.17 and 0.660, are from Table 2.2.) Since the sampling fractions are the same for terminal and primary branches when $n = 4.82 n'$, we will substitute $\frac{n}{4.82}$ for n' . Thus,

$$\frac{1.17}{n'} = \frac{(4.82)(1.17)}{n} = \frac{5.639}{n} .$$

Therefore, 5.639 compares with .660 when the sampling fractions are equal. The variance, 5.639, might be described as the relative variance among primary branches expressed on the basis of one terminal branch.

The conversion factor, 4.82, also applies to the other estimators. Thus, all of the unit variances for primary branches must be multiplied by 4.82 to convert them to the equivalent of one terminal branch. This leads to Table 2.3, which reflects differences in sampling efficiency under the condition that the sampling fraction is the same for primary and terminal branches and for all four plans.

The variances in Table 2.3 are also meaningful in terms of sampling fractions that would be required when all four estimators have the same variance. Such sampling fractions would be proportional to the variances in Table 2.3, assuming the fpc's are negligible. As an example, using primary branches as sampling units, the variance of \hat{y}_2 will be the same as the

variance of \hat{y}_1 when the sampling fraction of Plan 2 is 21 per cent, $\frac{1.191}{5.639} = .21$, of the sampling fraction for Plan 1. As another example, for the sampling variance of \hat{y}_3 using primary branches to be the same as the sampling variance of \hat{y}_4 using terminal branches, the sampling fraction would need to be 2.8, $\frac{0.897}{0.319}$, times larger.

Exercise 2.1 (a) Find the relative variance of \hat{y}_4 for a random sample of five terminal branches. Plan 4 is sampling with pps and replacement. Ans. 0.064.

(b) Assume simple random sampling of primary branches and find the number of primary branches so that the relative variance of $(\hat{y}_1) = 0.064$. The answer, ignoring the fpc, is 18.3. There were only 28 primary branches in the population so the fpc should be taken into account. Include the fpc, $\frac{N-n}{N}$, in the variance formula for \hat{y}_1 and recompute the sample size that is needed. Ans. 11 primary branches.

(c) With reference to (a) and (b), $135\hat{y}_4$ and $28\hat{y}_1$ are estimators of the population total number of apples. Will the relative variances of these two estimators of the total be equal when the sample sizes are 5 terminal branches with Plan 4 and 11 primary branches with Plan 1?

(d) It was stated above that, when the fpc is negligible, the variances in Table 2.3 are proportional to the sampling fractions needed to have the same relative variances of the estimates for all of the alternatives. The answers to (a) and (b) were $\frac{5}{135}$ and $\frac{18.3}{28}$ when the fpc was ignored. Verify

that these sampling fractions are proportional to the corresponding variances presented in Table 2.3.

Table 2.3 shows two major differences in efficiency:

(1) Plan 1 vs the other three plans and (2) primary vs terminal branches as sampling units. Table 2.4 presents the relative variances for Plans 2, 3 and 4 as a proportion of the variances for Plan 1. Notice that the proportions of the variation among primary branches which was accounted for by variation in the size (csa) of branches was much higher than the proportions for terminal branches. Variation in the size of terminal branches was partially controlled by the specifications and process for determining a terminal branch. For primary branches the correlation between X and Y was .91. It was .69 for terminal branches.

In Table 2.5 the variances for terminal branches are expressed as a proportion of the variances for primary branches. Here we see that the largest reduction in variance is under Plan 1. However, even after variance associated with variation in the csa has been taken into account in the estimator or process of selection (Plans 2, 3 and 4), the sampling variances for terminal branches are about one third of the sampling variances for primary branches. This is a manifestation of intra-class correlation--the general tendency for things that are close together in time or space to be alike. If there was no intra-class correlation, the sampling variances for Plans 2, 3 and 4 would have been about the same for primary and terminal branches. With Plan 1 the difference in variance between primary and terminal branches is attributable to the difference

in correlation between csa and number of apples as well as intra-class correlation.

The interaction shown in Table 2.3 between the variances for the four plans and the two kinds of sampling units seems typical. The situation might be viewed in this way. When the sampling units are large and auxiliary information is not used in the sample design or in estimation, the sampling variance is large and there is a large potential for reducing sampling variance. An auxiliary variable that is effective in reducing sampling variance will probably be relatively more effective when the sampling units are large. This was displayed in Table 2.4. Or, when an effective auxiliary variable is used, the relative difference in sampling variance between large and small sampling units will probably be less as displayed in Table 2.5.

The same phenomenon has been observed in various other situations. In area sampling, for example, if geographic stratification is effective, it will tend to be relatively more effective when the area sampling units are large than when they are small. This is not a justification for large sampling units. The implication is that matters of sample design and estimation are more critical when the sampling units are large and vary widely in size.

There is a limit to the reduction in variance that can be achieved through sample design and estimation techniques. That is, assuming a fixed sampling fraction, one might imagine

a practical minimum variance as a goal to be achieved by design. There might be a number of alternatives which will approach that goal. Table 2.3 shows three alternatives with relative variances between 0.3 and 0.4.

Exercise 2.2 Table 2.6, which will be discussed later, shows the number of apples on each of the six trees in the column headed Y_h . The variances among trees, $\frac{\Sigma(Y_i - \bar{Y})^2}{N-1}$, is 464,295, where Y_i is the number of apples on the i^{th} tree and N is the number of trees. Verify that the relative variance of Y_i is 0.344. This is the relative variance of \hat{y}_1 when a tree is the sampling unit and the size of the sample is one tree. Convert this variance, 0.344, to the equivalent of one terminal branch. Ans. 7.74. Compare the answer with the variances in Table 2.3 for Plan 1.

Exercise 2.3 Assume that a simple random sample of terminal branches on the six trees is to be selected and that $N\bar{y}$ is the estimator of the total number of apples on the six trees. Ignoring the fpc, how many terminal branches need to be selected so the variance of $N\bar{y}$ is equal to the variance of an estimate based on a random selection of one tree and a count of all apples on the tree? Assume that by is the estimator for the sample of one tree where y is the number of apples on the sample tree. Refer to exercise 2.2 for the variance among trees and to Table 2.2 for the variance among terminal branches. Ans. The variance of an estimate from a sample of 2 terminal branches is equal to the variance of an estimate from a sample

of one tree. There were 22.5 terminal branches per tree so 2 terminal branches is less than one-tenth of one tree. This result is typical of the low sampling efficiency of a large sampling unit. Moreover, it is very difficult to make an accurate count of all apples on a tree.

2.3 STRATIFICATION BY TREES

Table 2.6 presents variances, covariances, and other information for each of the six trees. These data pertain to terminal branches. They will be used to determine the variances for five different estimators based on stratified random sampling with trees as strata and a constant sampling fraction. Stratified sampling with pps within trees will also be considered which gives a total of six alternatives. For these six alternatives, designated as plans 6 through 11, we want to find sampling variances that are comparable with the variances presented in Table 2.2 for nonstratified sampling of terminal branches.

It is advantageous to become sufficiently familiar with sampling theory to avoid searching textbooks for a formula and checking it to be sure it is applicable. A formula as found in a textbook might be appropriate but need adaptation. By recalling a few things from the theory of random variables, correct variance formulas can be readily derived for finding the sampling variances for the sampling and estimation plans that follow.

For comparative purposes, relative variances are recorded in Table 2.7 for four plans that have been discussed and for six additional plans that will be discussed in the next section.

2.3.1 PLAN 6--MEAN ESTIMATOR

In Plan 6 the sample is allocated to trees (strata) in proportion to the number of terminal branches on the trees. You may notice that Plan 6 is the same as Plan 5 except that the strata are trees instead of size-of-branch classes. The estimator of the population mean, \bar{Y} , is

$$\hat{y}_6 = \sum_h \frac{N_h}{N} \bar{y}_h = \frac{N_1}{N} \bar{y}_1 + \dots + \frac{N_L}{N} \bar{y}_L \quad (2.2)$$

where $\bar{y}_h = \frac{\sum_i y_{hi}}{n_h}$ is the sample average for stratum h (i.e., the average number of apples per terminal branch on tree h),

h is the index for strata (trees),

i is the index for sampling units within stratum h (branches on tree),

N_h is the total number of sampling units (terminal branches) in stratum h,

$N = \sum N_h$ is the total number of sampling units in the population, and

n_h is the number of sampling units in the sample from stratum h (number of branches in the sample from tree h).

Exercise 2.4 Since the sample is stratified and allocated to strata in proportion to N_h , the estimator is a simple average of all values of y_{hi} in the sample. Show that this is true.

The estimator, \hat{y}_6 , was written as shown in Eq. (2.2) because, to find its variance, we need to consider it as a function of the stratum means. The weights $\frac{N_h}{N}$, are constant. Therefore, the variance of \hat{y}_6 depends on the variance of the stratum means. The sample from one stratum is independent of the sample from another stratum. Therefore, the stratum means, \bar{y}_h , are independent random variables, and the terms, $\frac{N_h}{N} \bar{y}_h$, in \hat{y}_6 are independent random variables. We know from the theory of random variables that the variance of the sum of independent random variables is the sum of the variances of the random variables. This gives the basis for writing the variance of \hat{y}_6 as follows:

$$V(\hat{y}_6) = \sum_h [V(\frac{N_h}{N} \bar{y}_h)] = V(\frac{N_1}{N} \bar{y}_1) + \dots + V(\frac{N_L}{N} \bar{y}_L)$$

We also know that the variance of a constant times a variable equals the square of the constant times the variance of the variable. Hence,

$$V(\hat{y}_6) = \sum_h [(\frac{N_h}{N})^2 V(\bar{y}_h)] = (\frac{N_1}{N})^2 V(\bar{y}_1) + \dots + (\frac{N_L}{N})^2 V(\bar{y}_L) \quad (2.3)$$

Next, we need an expression for the variance of \bar{y}_h . Since the sample within each stratum is a simple random sample, the variance of \bar{y}_h is as follows:

$$V(\bar{y}_h) = \left(\frac{N_h - n_h}{N_h}\right) \frac{S_{Yh}^2}{n_h} \quad (2.4)$$

where

$$S_{Yh}^2 = \frac{\sum_i (Y_{hi} - \bar{Y}_h)^2}{N_h - 1}$$

The subscript Y in S_{Yh}^2 is included to show that the variance refers to the variable Y. Later we will need to take the variance of X into account and will use S_{Xh}^2 to represent the variance of X within stratum h and S_{XYh} to represent the covariance of X and Y within stratum h.

For simplicity and convenience assume that the sampling fractions, $f_h = \frac{n_h}{N_h}$, are small so the fpc's, $\frac{N_h - n_h}{N_h}$, may be ignored. Thus, dropping the fpc and substituting the variance of \bar{y}_h in Eq. (2.3) gives:

$$V(\hat{y}_6) = \sum \left(\frac{N_h}{N}\right)^2 \frac{S_{Yh}^2}{n_h} = \left(\frac{N_1}{N}\right)^2 \frac{S_{Y1}^2}{n_1} + \dots + \left(\frac{N_L}{N}\right)^2 \frac{S_{YL}^2}{n_L} \quad (2.5)$$

Since the sampling specifications called for a constant sampling fraction, $\frac{n_h}{N_h}$ is constant from stratum to stratum which means that

$$\frac{n_1}{N_1} = \dots = \frac{n_L}{N_L} = \frac{n}{N}$$

where $\sum n_h = n$ and $\sum N_h = N$

Substituting $\frac{n}{N}$ for $\frac{n_h}{N_h}$ in Eq. (2.5) and simplifying the expression we obtain

$$V(\hat{y}_6) = \frac{1}{n} \sum \frac{N_h}{N} S_{Yh}^2 = \frac{1}{n} \left[\frac{N_1}{N} S_{Y1}^2 + \dots + \frac{N_L}{N} S_{YL}^2 \right] \quad (2.6)$$

Exercise 2.5 Perform the algebra that is necessary to go from Eq. (2.5) to Eq. (2.6).

For Plan 6, let

$$S_6^2 = \sum W_h S_{Yh}^2 = W_1 S_{Y1}^2 + \dots + W_L S_{YL}^2 \quad (2.7)$$

where $W_h = \frac{N_h}{N}$

Since S_{Yh}^2 will be replaced by corresponding variances that are involved later in Plans 7 and 8, let $S_{6h}^2 = S_{Yh}^2$ so the notation will reflect the number of the plan or estimator. Then Eq. (2.7) becomes

$$S_6^2 = \sum W_h S_{6h}^2 \quad (2.8)$$

and Eq. (2.6) simplifies to the following form

$$V(\bar{y}_6) = \left(\frac{1}{n}\right) S_6^2 \quad (2.9)$$

where S_6^2 is a weighted average of the within stratum variances. The values of S_{6h}^2 are recorded in Table 2.6 in the column headed S_{6h}^2 and the value of S_6^2 is 1367 which is recorded in the line labeled "Separate." The reason for calling this line "Separate" will be explained later.

For purposes of comparing variances for alternative plans the choice of a sample size is arbitrary. Previously, the sampling variances for alternative plans were compared assuming $n = 1$. Even though it is impossible to select a stratified random sample of only one unit, it is possible to let $n = 1$ in Eq. 2.9 and regard the variance of \hat{y}_6 as the sampling

variance for a hypothetical sample of one unit. As with simple random sampling, a stratified random sample of n units would have a sampling variance equal to $\frac{1}{n}$ times the sampling variance for a hypothetical stratified random sample of one unit--provided n is large enough so the n_h , which must be integers, are approximately in proportion to N_h . Remember, these numerical examples are being worked as though the sampling fraction, f_h , is constant and small.

Exercise 2.6 Calculate the variance of \hat{y}_6 assuming $n = 1$. In other words, find the value of S_6^2 . Also, calculate the relative variance of \hat{y}_6 when $n = 1$. Your answer should agree with the relative variance of \hat{y}_6 which is recorded in Table 2.7.

Exercise 2.7 Since \hat{y}_6 is an estimate of \bar{Y} , $N\hat{y}_6$ is an estimate of the population total. Find the standard error of $N\hat{y}_6$ for $n = 1$. Ans. 4991.

2.3.2 PLAN 7--RATIO ESTIMATORS BY STRATA

Plan 7 is the same as Plan 6 except that $(\bar{X}_h \frac{\bar{y}_h}{\bar{x}_h})$, instead of \bar{y}_h , is used in Eq. 2.2 as an estimator of the stratum mean, \bar{Y}_h . Thus,

$$\hat{y}_7 = \sum \frac{N_h}{N} (\bar{X}_h \frac{\bar{y}_h}{\bar{x}_h}) = \frac{N_1}{N} (\bar{X}_1 \frac{\bar{y}_1}{\bar{x}_1}) + \dots + \frac{N_L}{N} (\bar{X}_L \frac{\bar{y}_L}{\bar{x}_L}) \quad (2.10)$$

The derivation of the relative variance of \hat{y}_7 follows the derivation in Plan 6. Simply replace the variance of \bar{y}_h in

Eq. (2.3) with the variance of $(\bar{x}_h \frac{\bar{y}_h}{\bar{x}_h})$. The variance of $(\bar{x}_h \frac{\bar{y}_h}{\bar{x}_h})$, ignoring the fpc, is

$$V(\bar{x}_h \frac{\bar{y}_h}{\bar{x}_h}) = (\frac{1}{n_h}) S_{7h}^2$$

where $S_{7h}^2 = S_{Yh}^2 + R_h^2 S_{Xh}^2 - 2R_h S_{XYh}$

Notice that S_{7h}^2 is the same as S_2^2 in Table 1.1 except that S_{7h}^2 is a variance within stratum h rather than a variance over the whole population. Substituting S_{7h}^2 for S_{Yh}^2 in Eqs. (2.5), (2.6), and (2.7) leads to the following results:

$$V(\hat{y}_7) = (\frac{1}{n}) S_7^2 \tag{2.11}$$

where $S_7^2 = \Sigma W_h S_{7h}^2$

The values of S_{7h}^2 and S_7^2 are presented in Table 2.6.

Exercise 2.8 The estimator \hat{y}_7 , Eq. (2.10), was expressed in a form to show its similarity to \hat{y}_6 . Is there a modification of Eq. (2.10) that would be better for computing the value of \hat{y}_7 from sample data? How would you compute the value of \hat{y}_7 from a sample?

Exercise 2.9 From the data presented in Table 2.6, find the relative variance of \hat{y}_7 for $n = 1$. The answer, 0.279, is in Table 2.7. How would you explain why the sampling variance for \hat{y}_7 is less than the sampling variance for \hat{y}_6 ?

The sampling variance for Plan 2 (no stratification and the ratio estimator) was 0.382 compared with 0.279 for Plan 7 (stratification and separate ratio estimators by strata). The geometrical interpretation of the sum of squares for Plan 7 compared with Plan 6 is analogous to Plan 2 compared with Plan 1. Horizontal lines for Plan 6 (one for each tree) are replaced by lines through the origin and the stratum means of X and Y. With the ratio estimator, \hat{y}_7 , the effect of stratification depends on how much the ratio lines differ among strata. More will be said later about stratification and ratio estimators.

Exercise 2.10 Notice with reference to Eq. (2.10) that $N_h \bar{X}_h$ is the population total of X for stratum h. Let $X_h = N_h \bar{X}_h$ and substitute X_h in Eq. (2.10) which gives

$$\hat{y}_7 = \frac{1}{N} \sum X_h \frac{\bar{y}_h}{\bar{x}_h} = \frac{1}{N} [X_1 \frac{\bar{y}_1}{\bar{x}_1} + \dots + X_L \frac{\bar{y}_L}{\bar{x}_L}]$$

With \hat{y}_7 in this form, write a formula for the variance of \hat{y}_7 .

2.3.3 PLAN 8--REGRESSION ESTIMATORS BY STRATA

Plan 8 is like Plans 6 and 7 except that the regression estimator (see Plan 3, Chapter I) is used stratum by stratum. Thus, instead of Eq. (2.2) or (2.10) we have

$$\begin{aligned} \hat{y}_8 &= \sum \left\{ \frac{N_h}{N} [\bar{y}_h + b_h (\bar{X}_h - \bar{x}_h)] \right\} \\ &= \frac{N_1}{N} [\bar{y}_1 + b_1 (\bar{X}_1 - \bar{x}_1)] + \dots + \frac{N_L}{N} [\bar{y}_L + b_L (\bar{X}_L - \bar{x}_L)] \quad (2.12) \end{aligned}$$

In the derivation of the variance of \hat{y}_8 , the variance of $\bar{y}_h + b_h(\bar{X}_h - \bar{x}_h)$ replaces the variance of \bar{y}_h in Eq. (2.3). This leads to an equation for the variance of \hat{y}_8 which is similar to the variances of \hat{y}_6 and \hat{y}_7 . Thus,

$$V(\hat{y}_8) = \frac{1}{n} S_8^2 \quad (2.13)$$

where
$$S_8^2 = \sum W_h S_{8h}^2$$

and
$$S_{8h}^2 = S_{Yh}^2 (1 - r_h^2)$$

where r_h is the correlation between X and Y within stratum h.

Exercise 2.11 Find the relative variance of \hat{y}_8 for $n = 1$. Compare your result with the relative variance for \hat{y}_8 that is recorded in Table 2.7.

2.3.4 DISCUSSION OF PLANS 6, 7, and 8

Compare the estimators, \hat{y}_6 , \hat{y}_7 , and \hat{y}_8 , and their variances with \hat{y}_1 , \hat{y}_2 , and \hat{y}_3 , and their variances, Table 2.7. In essence each stratum in Plans 6, 7, and 8 is treated as a separate population and the estimators and their variances within each of the strata are combined using appropriate weights. Geometric interpretations of the sampling variances with reference to sums of squares is analogous to the interpretations given in Chapter I for Plans 1, 2, and 3. There is one line for each stratum and each of the estimators, \hat{y}_6 , \hat{y}_7 , and \hat{y}_8 .

Figure 2.3 presents a dot chart for each of the six trees. For each tree, the solid line is the ratio line involved in \hat{y}_7 and the broken line is the ratio line for \hat{y}_2 , no stratification. As recorded in Table 2.7, the relative variances of \hat{y}_7 and \hat{y}_2 are 0.279 and 0.382 respectively. This indicates the degree to which the 6 ratio lines fit the data better than the single line. Figures analogous to Fig. 2.3 could be prepared for \hat{y}_6 compared with \hat{y}_1 , for \hat{y}_8 compared with \hat{y}_3 , for \hat{y}_8 compared with \hat{y}_7 , etc.

Separate stratum estimators like \hat{y}_7 and \hat{y}_8 are seldom used in practice. However, Plans 7 and 8 were included for comparative purposes and further understanding of possible alternatives. There will be additional discussion of these plans after Plans 9, 10, and 11 have been presented.

2.3.5 PLAN 9--COMBINED RATIO ESTIMATOR

Instead of making a ratio estimate for each stratum and combining the separate stratum estimates, the data from the strata are combined before computing a ratio. Likewise, in Plan 10, results for individual strata are combined and used to determine a "combined regression estimator." This explains the two titles "Separate" and "Combined" in Table 2.6. The "Separate" line contains averages of within stratum variances for Plans 7, 8, and 11 which use separate stratum estimators. The entries in the "Combined" line pertain to the combined stratum estimators in Plans 9 and 10. The distinction between separate and combined is not applicable to the mean estimator, Plan 6.

S_6^2 is shown in both lines of the table.

The "combined ratio estimator" is

$$\hat{y}_9 = \bar{x} \frac{\bar{y}_s}{\bar{x}_s} \quad (2.14)$$

where

$$\bar{y}_s = \frac{\sum N_h}{N} \bar{y}_h$$

$$\bar{x}_s = \frac{\sum N_h}{N} \bar{x}_h$$

The letter "s" in \bar{y}_s and \bar{x}_s is used to indicate that \bar{y}_s and \bar{x}_s are means that pertain to a stratified random sample.

To find the variance of \hat{y}_9 , it is convenient to remember that the large sample approximation of the relative variance (RelVar) of the ratio of any two random variables u and v is

$$\text{RelVar}\left(\frac{u}{v}\right) = \text{RelVar}(u) + \text{RelVar}(v) - 2\text{RelCov}(u,v)$$

Therefore, since \bar{y}_s and \bar{x}_s are random variables we have

$$\text{RelVar}\left(\frac{\bar{y}_s}{\bar{x}_s}\right) = \text{RelVar}(\bar{y}_s) + \text{RelVar}(\bar{x}_s) - 2\text{RelCov}(\bar{y}_s, \bar{x}_s) \quad (2.15)$$

Exercise 2.12 Verify that the relative variance of \hat{y}_9 is equal to the relative variance of the ratio, $\frac{\bar{y}_s}{\bar{x}_s}$.

With reference to Eq. 2.15, notice that \bar{y}_s is the same as \hat{y}_6 . We found for Plan 6, Exercise 2.6, that the RelVar of \hat{y}_6 , and therefore of \bar{y}_s , was 0.512 for $n = 1$. The RelVar of \bar{x}_s is determined in the same way. According to Table 2.6, the average

within stratum variance of X is 0.2566 and $\bar{X}^2 = 2.0240$. Thus, $\text{RelVar}(\bar{x}_s)$ for $n = 1$ is $\frac{0.2566}{2.0240} = 0.127$.

Exercise 2.13 Find the average within stratum covariance of X and Y in Table 2.6. Then find the value of $\text{RelCov}(\bar{y}_s, \bar{x}_s)$ for $n = 1$. Ans. 0.166.

According to Eq. (2.15) the RelVar of $\frac{\bar{y}_s}{\bar{x}_s}$ is

$$0.512 + 0.127 - 2(0.166) = 0.307$$

Therefore, the RelVar of \hat{y}_g is 0.307. This answer is recorded in Table 2.7.

Exercise 2.14 Start with Eq. 2.15 and show that the variance of \hat{y}_g is given by

$$V(\hat{y}_g) = V(\bar{y}_s) + R^2 V(\bar{x}_s) - 2R[\text{Cov}(\bar{y}_s, \bar{x}_s)]$$

where $R = \frac{\bar{Y}}{\bar{X}}$. Suggestion: Notice that $V(\hat{y}_g) = \bar{Y}^2 [\text{RelVar}(\hat{y}_g)]$, then multiply the right hand side of Eq. (2.15) by \bar{Y}^2 . For $n = 1$ the value of $V(\bar{y}_s)$, $V(\bar{x}_s)$, $\text{Cov}(\bar{y}_s, \bar{x}_s)$ and R are given in the "Combined" line of Table 2.6. Using these values compute the value of $V(\hat{y}_g)$. The answer is 817, which is also in the "Combined" line.

Exercise 2.15 Beginning with the variance of \hat{y}_g as expressed algebraically in Exercise 2.14, show that

$$V(\hat{y}_g) = \frac{1}{n} S_g^2$$

where
$$S_9^2 = \sum_h W_h S_{9h}^2$$

and
$$S_{9h}^2 = S_{Yh}^2 + R^2 S_{Xh}^2 - 2RS_{XYh}$$

Suggestion: Since \bar{y}_s and \hat{y}_6 are the same you may refer to Eq. (2.9) to obtain the appropriate formula for $V(\bar{y}_s)$.

Formulas for $V(\bar{x}_s)$ and $\text{Cov}(\bar{x}_s, \bar{y}_s)$ are analogous. Compare S_{9h}^2 with S_{7h}^2 .

Exercise 2.16 Continuing from the formula for $V(\hat{y}_9)$ which is given in Exercise 2.15, show that

$$V(\hat{y}_9) = \frac{1}{n} \left[\sum_h W_h \frac{\sum_i (Y_{hi} - RX_{hi})^2}{N_h - 1} \right]$$

The formula for the variance of \hat{y}_9 , which is given in Exercise 2.16, shows that the deviations which are squared are deviations from a line through the origin and (\bar{X}, \bar{Y}) where \bar{X} and \bar{Y} are the overall means of X and Y . This line for the combined ratio estimator, \hat{y}_9 , is the same as the line pertaining to \hat{y}_2 , the ratio estimator without stratification. Thus, if \hat{y}_9 has a lower variance than \hat{y}_2 it is attributable to the effect of stratification which assures proportional representation in the sample by strata. That is, there is proportional representation by strata of the deviations of Y_i from the combined ratio line. In Plan 7 there was proportional representation and separate ratio lines by strata. RelVar of \hat{y}_9 was 0.307 compared to 0.382 for \hat{y}_2 and 0.279 for \hat{y}_7 (see Table 2.7).

2.3.6 PLAN 10--COMBINED REGRESSION ESTIMATOR

As in the case of the combined ratio estimator, data for strata may be combined and a single (or combined) regression used instead of separate regressions. The estimator, \hat{y}_{10} , for the combined regression looks like \hat{y}_3 but it is an average within stratum regression that is determined from combined within stratum variances and covariances. Since the sampling fraction is constant, the appropriate weights for combining the within stratum variances and covariances are $\frac{N_1}{N}, \dots, \frac{N_L}{N}$ which are the same weights used previously for combining variances. The combined within stratum variances of Y and X, 1367 and .2566, and the combined within stratum covariance, 12.23, are shown in the "Combined" line of Table 2.6. These numbers are needed for computing the "Combined" regression coefficient, the "Combined" correlation coefficient, and the variance of \hat{y}_{10} for $n = 1$, which are also shown in the "Combined" line of Table 2.6. The corresponding numbers for sampling without stratification are shown in the last line of Table 2.6.

Algebraically

$$\hat{y}_{10} = \bar{y}_s + b_s (\bar{X} - \bar{x}_s) \quad (2.16)$$

where

$$b_s = \frac{\bar{S}_{XY}}{\bar{S}_X^2}$$

$$\bar{S}_{XY} = \sum_h W_h S_{XYh}$$

$$\bar{S}_X^2 = \sum_h W_h S_{Xh}^2 \quad \text{and}$$

$$W_h = \frac{N_h}{N}$$

Notice that lower case letters, x and y , are used in the definition of b_s to indicate that it is computed from sample values. In Table 2.6, the value of B_s is shown which is the population value that b_s is an estimate of. The bar in the expression \bar{S}_{XY} and \bar{S}_X^2 indicates that \bar{S}_{XY} and \bar{S}_X^2 are averages of within stratum covariances and variances. (Previously, we had used S_Y^2 , S_X^2 , and S_{XY} to represent the overall variances and covariances without stratification.) The subscript "s" is used as a code indicating that stratified random sampling and combined-stratum estimation are involved. To recapitulate, b_h is a least squares estimate of the regression coefficient within stratum h , b_s is an estimate of the combined regression coefficient in the combined regression estimator, and b is the least-squares regression coefficient computed from a simple random sample without stratification.

The variance of \hat{y}_{10} is

$$V(\hat{y}_{10}) = \left(\frac{1}{N}\right)S_{10}^2 \quad (2.17)$$

where

$$S_{10}^2 = \bar{S}_Y^2 (1-r_s^2)$$

$$\bar{S}_Y^2 = \sum_h W_h S_{Yh}^2$$

and

$$r_s = \frac{\bar{S}_{XY}}{\sqrt{\bar{S}_X^2 \bar{S}_Y^2}}$$

The variance of \hat{y}_{10} involves squares of the deviations of Y_i from a line with a slope equal to B_s that passes through (\bar{X}, \bar{Y}) .

Remember the assumptions and that the variance formula is a large sample approximation. Further discussion of the basis for the formula for the variance of \hat{y}_{10} will be omitted. For more detail the reader is referred to Cochran.^{4/}

Exercise 2.17 Verify that the regression coefficient for the combined within stratum regression is 47.7 and that the combined within stratum correlation coefficient is 0.653. Then verify that the relative variance of \hat{y}_{10} is 0.294 for $n = 1$.

2.3.7 PLAN 11--SAMPLING WITH PPS WITHIN STRATA

As in Plan 4, sampling with replacement is assumed for simplicity. That is, in stratum h the probability of the i^{th} sampling unit being selected on any given draw is proportional to X_{hi} . The estimator is

$$\hat{y}_{11} = \sum_h \left(\frac{N_h}{N} \right) \hat{y}_{11h} \quad (2.18)$$

where

$$\hat{y}_{11h} = \left(\frac{\bar{X}_h}{n_h} \right) \sum_i \frac{y_{hi}}{x_{hi}}$$

Notice that \hat{y}_{11h} is like \hat{y}_4 , the difference being that \hat{y}_{11h} is an estimate of the stratum mean \bar{Y}_h whereas \hat{y}_4 is an estimate of the population mean \bar{Y} . Also, notice that the estimator, \hat{y}_{11} , can be obtained by substituting \hat{y}_{11h} for \bar{y}_h in Eq. 2.2.

^{4/} Cochran, W. G., Sampling Techniques, Second Edition, Chapter 7. John Wiley & Sons, Inc., 1963.

It follows that the variance of \hat{y}_{11} can be obtained by substituting the variance of \hat{y}_{11h} for the variance of \hat{y}_h in Eq. (2.3).

Owing to the similarity of \hat{y}_{11h} and \hat{y}_4 the formula for the variance of \hat{y}_4 is applicable. Simply add a subscript h in the formula for the variance of \hat{y}_4 , which gives

$$V(\hat{y}_{11h}) = \left(\frac{1}{n_h}\right) \left(\frac{1}{N_h^2}\right) \sum_i P_{hi} \left(\frac{Y_{hi}}{P_{hi}} - Y_h\right)^2$$

where $P_{hi} = \frac{X_{hi}}{X_h}$

$$Y_h = \frac{\sum_i Y_{hi}}{i}$$

and $X_h = \frac{\sum_i X_{hi}}{i}$

Substitution of $V(\hat{y}_{11h})$ in Eq. (2.3) gives

$$V(\hat{y}_{11}) = \sum_h \left(\frac{N_h}{N}\right)^2 \left[\left(\frac{1}{n_h}\right) \left(\frac{1}{N_h^2}\right) \sum_i P_{hi} \left(\frac{Y_{hi}}{P_{hi}} - Y_h\right)^2 \right] \quad (2.19)$$

As in the derivation of 2.6, assume that n_h is proportional to N_h , which means that $n_h = \left(\frac{n}{N}\right)N_h$. Substituting $\left(\frac{n}{N}\right)N_h$ for n_h in Eq. (2.19) leads to the following which expresses the variance of \hat{y}_{11} in a form like that used for the other estimators:

$$V(\hat{y}_{11}) = \left(\frac{1}{n}\right) S_{11}^2 \quad (2.20)$$

where $S_{11}^2 = \sum_h W_h S_{11h}^2$

and $S_{11h}^2 = \frac{1}{N_h^2} \sum_i P_{hi} \left(\frac{Y_{hi}}{P_{hi}} - Y_h\right)^2$

Like the variances for the other estimators, S_{11}^2 is a weighted average of the appropriate within stratum variances. The within stratum variances, S_{11h}^2 , are presented in Table 2.6 and S_{11}^2 , the variance of \hat{y}_{11} for $n = 1$, is recorded in the "separate" line.

Exercise 2.18 Using the data in Table 2.1, find the value of S_{11h}^2 for $h = 1$. Check your answer with the value recorded in Table 2.6. Is there a better expression than the one given above for finding the values of S_{11h}^2 ?

Exercise 2.19 From the data by individual trees that are presented in Table 2.6, find the RelVar of \hat{y}_{11} for $n = 1$ and check your answer with the value of S_{11}^2 that is recorded in Table 2.7.

A geometrical interpretation of the variance of \hat{y}_{11} is a matter of making an interpretation for each stratum and judging the average situation over all strata. For this purpose reference is made to the discussion of \hat{y}_4 in Chapter I.

2.3.8 SUMMARY AND DISCUSSION

Sampling variances for 10 out of 11 plans are presented in Table 2.7 for terminal branches as sampling units. Plan 5 was not applied to terminal branches. All of the plans have an important practical shortcoming. It is necessary to define, label, and list all terminal branches on a tree before it is sampled. Some ways of avoiding this will be discussed in Chapter III. However, Chapter II was intended as an exercise

in the use of theory to find the variances for alternative sampling and estimation plans and as a study of the differences in the variances for several alternatives.

As you gain experience through evaluations of sampling plans you will become increasingly aware of prevailing patterns of variation. You will observe manifestations of the general tendency for things to be stratified in space or time, or the tendency for things that are close together in space or time to be alike. There are exceptions. For example, in a field where the plant population is very dense there might be a negative intra-plot correlation among plants within very small plots owing to competition between adjacent plants.

From the results in Table 2.7 we find that the two plans with the largest variance are Plans 1 and 6. Neither plan makes use of size of branch as an auxiliary variable. The reductions in variance from use of csa as an auxiliary variable are substantial. This strongly suggests exploration of practical ways of using csa as a measure of branch size unless it is possible and feasible, when determining terminal branches, to restrict the sizes within narrow limits.

The variances for "separate" ratio and regression estimators are moderately less than the corresponding variances for the "combined" ratio and regression estimators. A small difference in favor of "separate" estimators is indicated by general experience and mathematical considerations. However, "combined" ratio or regression estimators are generally used

in practice because: (1) they are more convenient; (2) in some situations, bias in the "separate" estimators is appreciable relative to the standard error; and (3) the variance formulas, which are large sample approximations, are better approximations for the "combined" estimators. Separate ratio or regression estimators might be preferable to combined estimators when the number of strata is very small and the ratios or regressions differ widely among the strata.^{5/}

With stratified random sampling, sampling variance is a function of variation within strata. It is generally better to judge the impact of stratification by considering within stratum variation than by the differences among strata. Making a choice between two alternative methods of stratification solely on the basis of differences among strata could in some cases be misleading. For example, the variance among the means of four strata could be much larger than the variance among the means of 30 strata. That does not necessarily mean that the sampling variance for the four strata will be the least. Also, the effect of stratification and of optimum allocation among strata are not independent of the method of estimation.

In the preceding discussion, stratification was considered as a matter of reducing sampling variance. In the design of a sample for a survey, attention needs to be given to the domains (subpopulations) for which estimates are important.

^{5/} See Cochran, Sampling Techniques, for a discussion of the properties of the separate and combined estimators.

This might be a primary determiner of the stratification and allocation of the sample. The sampling variances of domain estimates depend, among other things, on how close the boundaries of strata for sampling purposes correspond to the domains for which estimates are required.

2.4 FURTHER COMPARISON OF SAMPLING WITH PPS TO STRATIFIED SAMPLING WITH OPTIMUM ALLOCATION

In Chapter 1, sampling with PPS was compared to stratified random sampling with optimum allocation to strata. The data for terminal branches provide a better set of data for study of sampling with pps including the possibility of a transformation of X or Y to reduce sampling variance. For this purpose, five size-of-branch strata based on c_{sa} will be used. Table 2.8 shows the definition of these strata and presents key information about the five strata. (Reference is made to Sections 1.2.5, 1.2.6, and 1.3.1 on sampling with pps and stratified random sampling with optimum allocation.) For stratified random sampling using the mean estimator, Eq. 2.2, the optimum sampling fraction for stratum h is given by

$$f'_h = \left(\frac{S_{Yh}}{\sum N_h S_{Yh}} \right) n$$

In previous comparisons we assumed $n = 1$. Hence, we are interested in the values of

$$f'_h = \frac{S_{Yh}}{\sum N_h S_{Yh}} \quad (2.21)$$

which are presented in Table 2.9. The values of f'_h are the sampling fractions within strata for a hypothetical sample of one branch and are comparable to the probabilities $P_i = \frac{X_i}{X}$ for selecting one branch with pps, where X_i is the csa of the i^{th} branch and $X = \sum N_i X_i$. Let P_h equal the average value of P_i for the branches in stratum h . The values of P_h are presented in Table 2.9 for comparison with values of f'_h .

Exercise 2.20 Verify the values of f'_h and P_h in Table 2.9 for one or two of the strata. The data presented in Table 2.8 are sufficient for this purpose.

The values of f'_h and P_h agree quite well, which means the probability of a branch being in a sample is roughly the same for both methods, except for variation of P_i within a stratum. The next question is how well do the lines that are involved fit the data. Turn to Figure 2.4. The points appear to fit horizontal lines (which are not shown) for stratified random sampling approximately as well as the line through the origin and (\bar{X}, \bar{Y}) for pps.

The variance for sampling with pps, Plan 4, has already been obtained. According to Table 2.2 it is 0.319. For the stratified sampling with optimum allocation, which will be called Plan 12, the estimator of \bar{Y} is

$$\hat{y}_{12} = \left(\frac{1}{N}\right) \sum N_h \bar{y}_h \quad (2.22)$$

and the variance of \hat{y}_{12} is given by

$$V(\hat{y}_{12}) = \frac{1}{n}(S_{12}^2) \quad (2.23)$$

where

$$S_{12}^2 = \left(\frac{\sum N_h S_{Yh}}{N} \right)^2$$

Exercise 2.21 Using the data in Table 2.8, find the RelVar of \hat{y}_{12} for $n = 1$. Ans. 0.273.

Exercise 2.22 From Eqs. (2.5) and (2.21) derive algebraically the variance of \hat{y}_{12} which is given by 2.23.

In this example, the RelVar for stratified random sampling with optimum allocation was 0.273 compared with 0.319 for sampling with pps. The difference in variance is attributable to the difference in probabilities of selection and to how well the lines that are implicitly involved fit the data.

A question posed earlier was whether some transformation of X might provide a better measure of size for pps sampling. A simple transformation would be $X'_i = X_i + C$, where C is a constant and X'_i is the transformed variable. The least squares regression line, see Figure 2.4, crosses the horizontal axis at 0.46. Since the least squares line fits the data "better" than any other straight line the transformation $X_i - 0.46$ is suggested. With this transformation the least squares and pps lines become the same. But, with the transformation $X_i - 0.46$ the maximum values of Y_i do not approach zero as $X'_i = X_i - 0.46$ approaches zero which indicates that the transformation is not a good one. However, it is informative to

make the transformation. Instead of $P'_i = \frac{X'_i}{\bar{X}}$, we now have

$P'_i = \frac{X'_i - 0.46}{\Sigma(X_i - 0.46)}$. The average values of P'_i within strata,

which are labeled P'_h , are presented in Table 2.9 for comparison with the values of P_h and the optimum sampling fractions, f'_h .

When X_i is used as the auxiliary variable, the relative variance is 1.403 compared to 0.319 when X_i is the auxiliary variable. The relative variance for Plan 1 was only 0.660. Thus, the transformed variable X'_i results in an increase in variance compared to simple random sampling with equal probabilities of selection. Before transformation, the selection probabilities for sampling with pps were .0032 and .0140 for the smallest and largest branches and were .0012 and .0171 after transformation. Thus, the range in the selection probabilities were greatly increased by the transformation from a factor of $4.3 = \frac{.0140}{.0032}$ to a factor of $14.2 = \frac{.0171}{.0012}$. The transformation does not effect the optimum sampling fractions, f'_h .

Exercise 2.23 Verify two of the values of P'_h that are presented in Table 2.9.

Exercise 2.24 Verify that when the transformation $X'_i = X_i - 0.46$ is made the pps line and the least squares regression line become the same.

With reference to Figure 2.4, consider two lines through the origin that represent maximum and minimum values of Y . (See Figure 1.2 in Chapter I which was portrayed as a good case for pps). As an approximation, theory suggests that a good measure of size is one that is proportional to the difference between two lines representing the maximum and minimum values of Y . A look at Figure 2.4 with this in mind suggests that a transformation such as $X'_i = X_i - 0.46$ is not a good possibility for reducing variance.

Exercise 2.25 Refer to Table 2.8 and for each stratum divide S_{Yh} by \bar{X}_h and examine S_{Yh} as a proportion of \bar{X}_h . Does this indicate that a transformation of X would be advisable?
Ans. No. A transformation of X is not indicated and one should accept csa as a measure of size unless there is evidence to the contrary from other sources.

Table 2.10 provides a comparison of variances for four plans when X and $X' = X - 0.46$ are the auxiliary variables.

Exercise 2.26 Explain why the transformation of X to X' has no effect on the variances for Plans 3 and 12.

Exercise 2.27 From the data presented in the last line of Table 2.6, compute the RelVar of the ratio estimator (Plan 2) after the transformation, that is, when $X'_i = X_i - 0.46$ is used as an auxiliary variable instead of X_i . Notice that a transformation of this kind does not affect the variance or covariance, but the value of R is changed.

We have established that the csa of a branch is a good measure of size with regard to probabilities of selection. Judging from Figure 2.4, the least squares line and the ratio line differ enough to raise a question of transforming Y instead of X. It would be possible to add a constant to Y so the least squares regression line for X and Y' (where Y' = Y+C) would pass through the origin and be the same as the ratio line involving X and Y'. Such a transformation would not change the selection probabilities and it appears that an appreciable reduction in variance might be obtained.

Exercise 2.28 Find the value of C in Y' = Y+C such that the regression line for X and Y' will pass through the origin.

Ans. C = 24.

Consider the result from Exercise 2.28 and the transformation Y' = Y + 24. The estimator of \bar{Y} , without stratification, would be

$$\hat{y} = \frac{1}{n} (\bar{X}) \left(\sum_i^n \frac{y_i + 24}{x_i} \right) - 24$$

The RelVar of \hat{y} is 0.294 which is about 8 percent less than 0.319, the RelVar for Plan 4. If it is necessary to estimate C from the sample, the variance of C must be taken into account and there is no gain from the transformation. However, if there is good prior information about the value of C, the possibility of the transformation Y+C might be worth considering.

When considering sampling with pps, look for a measure of size that is close to being proportional to Y_i . If Y_i is

exactly proportional to X_i , the ratio $\frac{Y_i}{X_i}$ is constant and the sampling variance is zero. Also, the situation is a good one for sampling with pps when the standard deviation of Y for a fixed value of X is proportional to the value of X .

In stratified random sampling some statisticians, in the absence of a better basis, allocate a sample to strata according to estimates of the proportion of the total that each stratum accounts for. For example, stratum 5 accounts for 23 percent, $\frac{1634}{6973}$, of the apples so 23 percent of the sample would be allocated to stratum 5. Only 8 percent of the sample would be allocated to stratum 1 even though it contains 21 percent of the branches. In practice, prior data often provide an estimate of the proportion of the population total that each stratum accounts for. Thus, the size of sample, n_h'' , for stratum h would be

$$n_h'' = P_h'' n \quad (2.24)$$

where P_h'' is the proportion that stratum h accounts for and n is the total size of the sample. The sampling fraction for stratum h is

$$f_h'' = \left(\frac{n_h''}{N_h} \right) = \left(\frac{P_h''}{N_h} \right) n$$

and for $n = 1$

$$f_h'' = \frac{P_h''}{N_h}$$

Thus, $f_h'' = \frac{P_h''}{N_h}$ compares with the sampling fractions (or selection probabilities) for the methods discussed previously. Values of f_h'' for the numerical example on apples are in Table 2.9.

Exercise 2.29 Verify two of the values of f_h'' .

Allocating a sample to strata in proportion to prior estimates of the amounts that the strata account for is a good plan where the coefficients of variations of Y are nearly constant among strata. In Table 2.8 notice that the coefficient of variations tend to decrease as the branch size increases. This phenomena appears very frequently. The fact that the first stratum has the highest coefficient of variation means that the sample for the first stratum should be larger than n_h'' , given by Eq. 2.24. This is also indicated by the comparison of f_h' and f_h'' . As a "rule of thumb," some statisticians have adopted a practice of allocating a sample according to (2.24) and then doubling the size of the sample for the first stratum and increasing the sample for the second stratum by 50 percent. Small departures from an optimum allocation have a negligible impact on variance. Moreover, in practice an exact optimum allocation cannot be achieved because exact values of within stratum variances are unknown.

Table 2.1--Number of Apples and Cross Section Areas
(Terminal Branches)

Tree No. 1		Tree No. 2		Tree No. 3		Tree No. 4		Tree No. 5		Tree No. 6	
CSA	No. of Apples	CSA	No. of Apples	CSA	No. of Apples	CSA	No. of Apples	CSA	No. of Apples	CSA	No. of Apples
X	Y	X	Y	X	Y	X	Y	X	Y	X	Y
.62	2	1.83	67	2.68	206	1.93	97	1.20	30	1.09	42
.97	15	1.99	45	.97	32	2.41	165	2.15	41	.87	25
1.27	12	1.12	51	1.48	73	2.24	124	.97	10	1.47	56
.72	32	1.93	54	2.32	138	2.41	143	1.15	8	1.91	116
.62	14	3.26	116	1.83	133	2.07	58	1.27	40	1.09	27
.97	5	1.14	51	.97	32	1.54	75	1.15	14	1.15	46
.87	8	1.34	80	1.03	30	1.47	59	1.15	36	.62	2
.72	9	.87	0	1.43	27	1.43	92	.87	0	2.24	112
1.01	11	.92	58	2.24	88	1.47	82	.72	15	1.76	83
.97	7	1.76	19	.92	42	1.29	58	.92	2	.87	36
1.83	59	1.15	45	1.99	109	1.09	30	.67	13	.67	35
.87	5	1.17	33	1.47	74	1.21	36	1.54	57	1.03	59
1.03	34	1.03	41	1.64	56	.76	24	1.21	31	1.22	29
		.62	42	1.54	116	2.41	230	1.61	8	1.00	25
		1.14	12	1.99	124	.72	35	1.54	32	1.09	61
		1.27	25	1.83	79	1.03	75	1.54	26	1.09	27
		2.41	54	1.47	30	1.91	128	1.83	18	1.54	59
		1.27	14	1.21	31	1.18	0	1.83	17	1.34	25
		1.35	35	1.91	41	1.16	47	1.34	4	1.68	77
		1.07	39	1.47	16	1.15	34			2.68	120
		1.03	30	1.15	23					1.40	59
		1.91	28	1.40	35					2.07	64
		2.07	129	1.42	61					1.47	83
		1.67	108	1.76	116					1.21	19
		1.61	123	3.26	88					1.83	16
		1.61	63	2.59	50					1.03	26
		1.27	26							.97	50
										.62	36
										1.27	48
										1.99	65

$N_1 = 13$

73

$N_2 = 27$

$N_3 = 26$

$N_4 = 20$

$N_5 = 19$

$N_6 = 30$

$$S_Y^2 = \frac{\sum(Y_i - \bar{Y})^2}{N-1} = 1762$$

$$S_X^2 = \frac{\sum(X_i - \bar{X})^2}{N-1} = .2890$$

$$S_{XY} = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{N-1} = 15.46$$

$N = 135$

$\sum Y = 6973$

$\sum X = 192.06$

$R = 36.31$

$r = .6850$

$B = 53.49$

Table 2.2--Relative Variances of Numbers of Apples Among
Primary and Terminal Branches

<u>Plan</u>	<u>Estimator</u>	<u>Relative Variances Among</u>	
		<u>Primary Branches</u>	<u>Terminal Branches</u>
1	\hat{y}_1	1.17	0.660
2	\hat{y}_2	0.247	0.382
3	\hat{y}_3	0.186	0.350
4	\hat{y}_4	0.194	0.319

Table 2.3--Relative Variances of Numbers of Apples Expressed
in Terms of One Terminal Branch

<u>Plan</u>	<u>Estimator</u>	<u>Relative Variances Among</u>	
		<u>Primary Branches</u>	<u>Terminal Branches</u>
1	\hat{y}_1	5.639	0.660
2	\hat{y}_2	1.191	0.382
3	\hat{y}_3	0.897	0.350
4	\hat{y}_4	0.935	0.319

Table 2.4--Relative Variances Expressed as a Proportion of the Variances for Plan 1

<u>Plan</u>	<u>Primary Branches</u>	<u>Terminal Branches</u>
1	1.00	1.00
2	0.21	0.58
3	0.16	0.53
4	0.17	0.48

Table 2.5--Relative Variances for Terminal Branches as a Proportion of the Variances for Primary Branches

<u>Plan</u>	<u>Primary Branches</u>	<u>Terminal Branches</u>
1	1.00	0.12
2	1.00	0.32
3	1.00	0.39
4	1.00	0.34

Table 2.6--Data for Six Trees ^{1/}

Tree	N_h	Y_h	X_h	S_{6h}^2 (Also S_{Yh}^2)	S_{Xh}^2	S_{XYh}	R_h	S_{7h}^2	r_h	S_{8h}^2	B_h	S_{11h}^2	
51	1	13	213	12.47	259	0.1019	3.50	17.08	169	0.681	139	34.3	139
	2	27	1388	39.81	1147	0.3089	10.10	34.88	818	0.537	816	32.7	772
54	3	26	1850	43.97	2184	0.3301	16.64	42.07	1368	0.620	1344	50.4	1120
	4	20	1592	30.88	3106	0.2996	25.67	51.55	1256	0.842	904	85.7	1038
	5	19	402	24.66	241	0.1563	2.66	16.30	196	0.433	196	17.0	182
	6	30	1528	40.27	892	0.2479	11.22	37.95	397	0.755	384	45.3	364
Separate ^{2/}	N			S_6^2				S_7^2		S_8^2		S_{11}^2	
	135	xxxx	xxxxxx	1367	xxxxxxx	xxxxxx	xxxxxx	745	xxxxxx	682	xxxx	644	
Combined ^{3/}	N	Y	X	S_6^2	\bar{S}_X^2	\bar{S}_{XY}	R	S_9^2	R_s	S_{10}^2	B_s		
	135	6973	192.06	1367	0.2566	12.33	36.31	817	0.653	784	47.7	xxxx	
Overall ^{4/}	N	Y	X	S_1^2	S_X^2	S_{XY}	R	S_2^2	r	S_3^2	B	S_4^2	
	135	6973	192.06	1762	0.2890	15.46	36.31	1020	0.685	935	53.49	852	

^{1/} See text for explanation of symbols.

^{2/} Results in this line pertain to separate stratum estimators. S_6^2 , S_7^2 , S_8^2 , are averages of the corresponding within stratum variances using $\frac{N_h}{N}$ as weights. See Equations 2.6 and 2.7 and Exercise 2.13.

^{3/} Results in this line pertain to combined stratum estimators, \hat{y}_9 and \hat{y}_{10} .

^{4/} No stratification. Results pertain to the first four plans.

Table 2.7--Summary of Sampling Plans--Estimators and Their Relative Variances for a Sample of One Terminal Branch

Plan	Method of Sampling	1/	Estimator	2/	Relative Variance for n = 1
1	A	mean	$\hat{y}_1 = \bar{y}$		0.660
2	A	ratio	$\hat{y}_2 = \bar{X} \frac{\bar{Y}}{\bar{x}}$		0.382
3	A	regression	$\hat{y}_3 = \bar{y} + b (\bar{X} - \bar{x})$		0.350
4	B	p.p.s	$\hat{y}_4 = \bar{X} \left(\frac{1}{n} \right) \sum \frac{y_i}{x_i}$		0.319
6	C	mean	$\hat{y}_6 = \bar{y} = \frac{1}{N} \sum N_h \bar{y}_h$		0.512
7	C	separate ratios	$\hat{y}_7 = \frac{1}{N} \sum X_h \frac{\bar{y}_h}{\bar{x}_h}$		0.279
8	C	separate regressions	$\hat{y}_8 = \sum \frac{N_h}{N} [\bar{y}_h + b_h (\bar{X}_h - x_h)]$		0.256
9	C	combined ratio	$\hat{y}_9 = \bar{X} \frac{\bar{y}_s}{\bar{x}_s}$		0.307
10	C	combined regression	$\hat{y}_{10} = \bar{y}_s + b_s (\bar{X} - \bar{x}_s)$		0.294
11	D	p.p.s	$\hat{y}_{11} = \sum_h \frac{N_h}{N} \left(\frac{\bar{X}_h}{n_h} \right) \sum \frac{y_i}{x_i}$		0.241

- 1/ A Simple random sampling without stratification
 B Sampling with replacement and p.p.s without stratification
 C Simple random sampling within strata (trees)
 D Sampling with p.p.s within strata (trees)

2/ h is the index to strata
 s as in \bar{y}_s refers to stratification. Thus \bar{y}_s is the mean of a stratified random sample and \bar{y} is the mean of a simple random sample.

Table 2.8--Data for Size-of-Branch Strata

<u>Stratum</u>	<u>Branch Size</u>	<u>No. of Branches</u>	\bar{X}_h	<u>No. of Apples</u>	\bar{Y}_h	S_{Yh}	$\frac{S_{Yh}}{\bar{Y}_h}$
1	.60-1.00	28	0.816	586	20.93	16.79	0.80
2	1.01-1.40	45	1.161	1500	33.33	17.22	0.52
3	1.41-1.80	28	1.543	1765	63.04	31.42	0.50
4	1.81-2.20	21	1.935	1488	70.86	39.53	0.56
5	2.21+	13	2.550	1634	125.69	52.72	0.42
Total or Average		135	1.423	6973	51.65		

Table 2.9--Sampling Fractions

<u>Stratum</u>	f'_h	P_h	P'_h	f''_h
1	.0046	.0042	.0027	.0030
2	.0047	.0060	.0054	.0048
3	.0086	.0080	.0083	.0090
4	.0109	.0101	.0113	.0102
5	.0145	.0133	.0161	.0180

Table 2.10--Effect of Transformation

<u>Estimator</u>	<u>Plan</u>	<u>Relative Sampling Variance</u>	
		<u>Before Transformation</u>	<u>After Transformation</u>
Ratio(no stratification)	2	0.382	0.350
Regression(no stratification)	3	0.350	0.350
PPS (no stratification)	4	0.319	1.403
Mean (stratification by size)	12	0.273	0.273

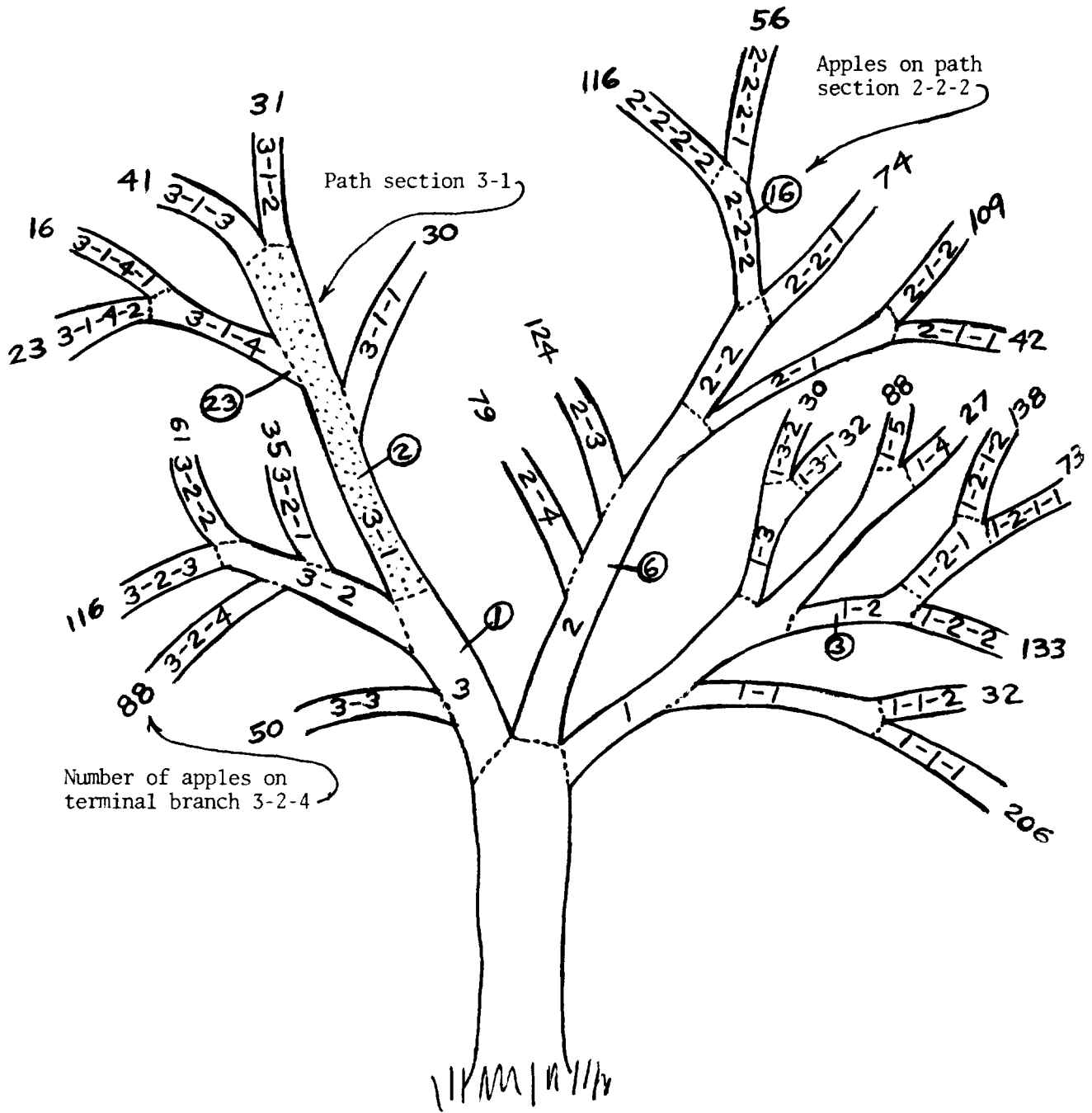


Figure 2.1--Map of apple tree no. 3 showing branch identification and number of apples

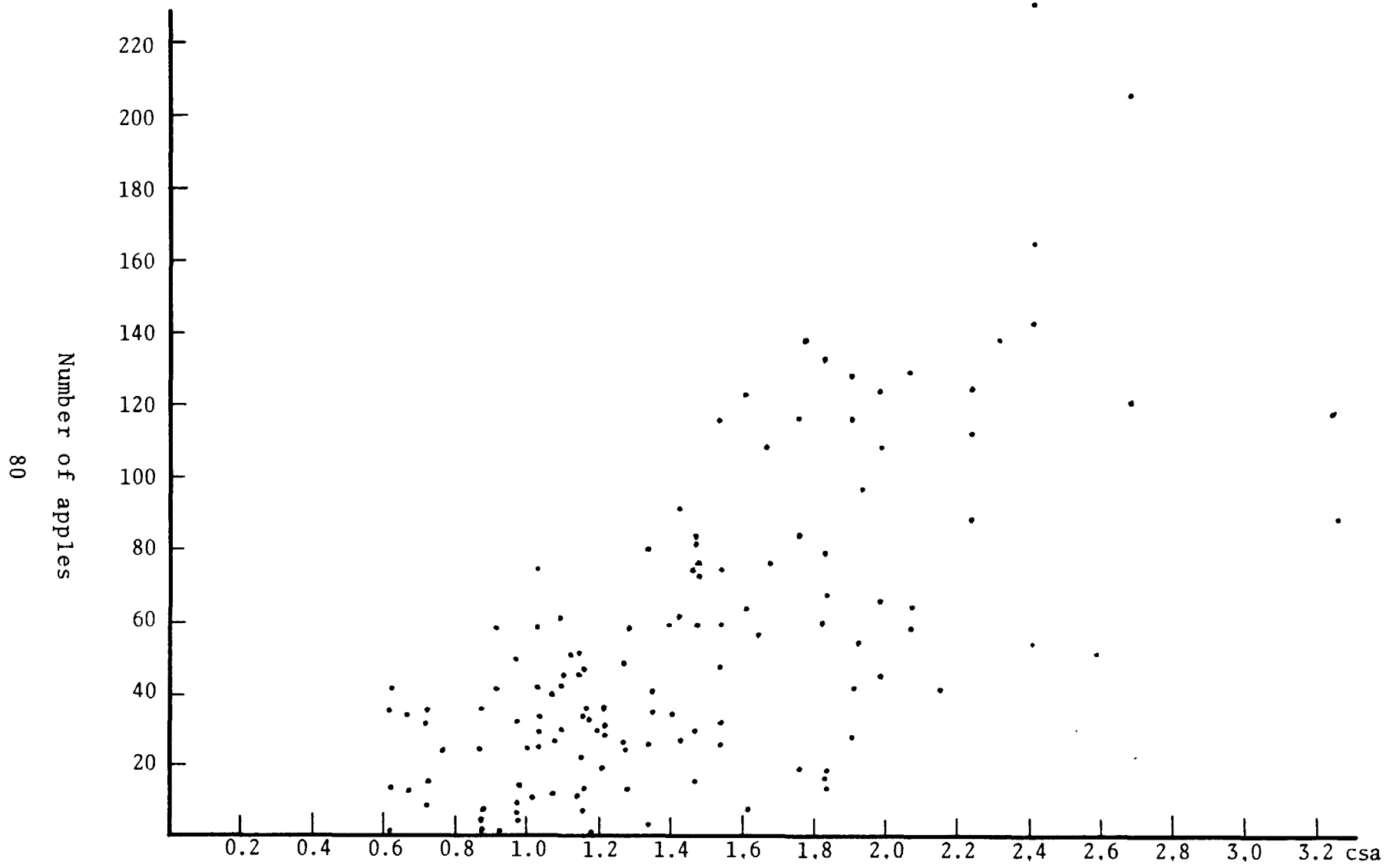


Figure 2.2--Number of apples by csa---terminal branches

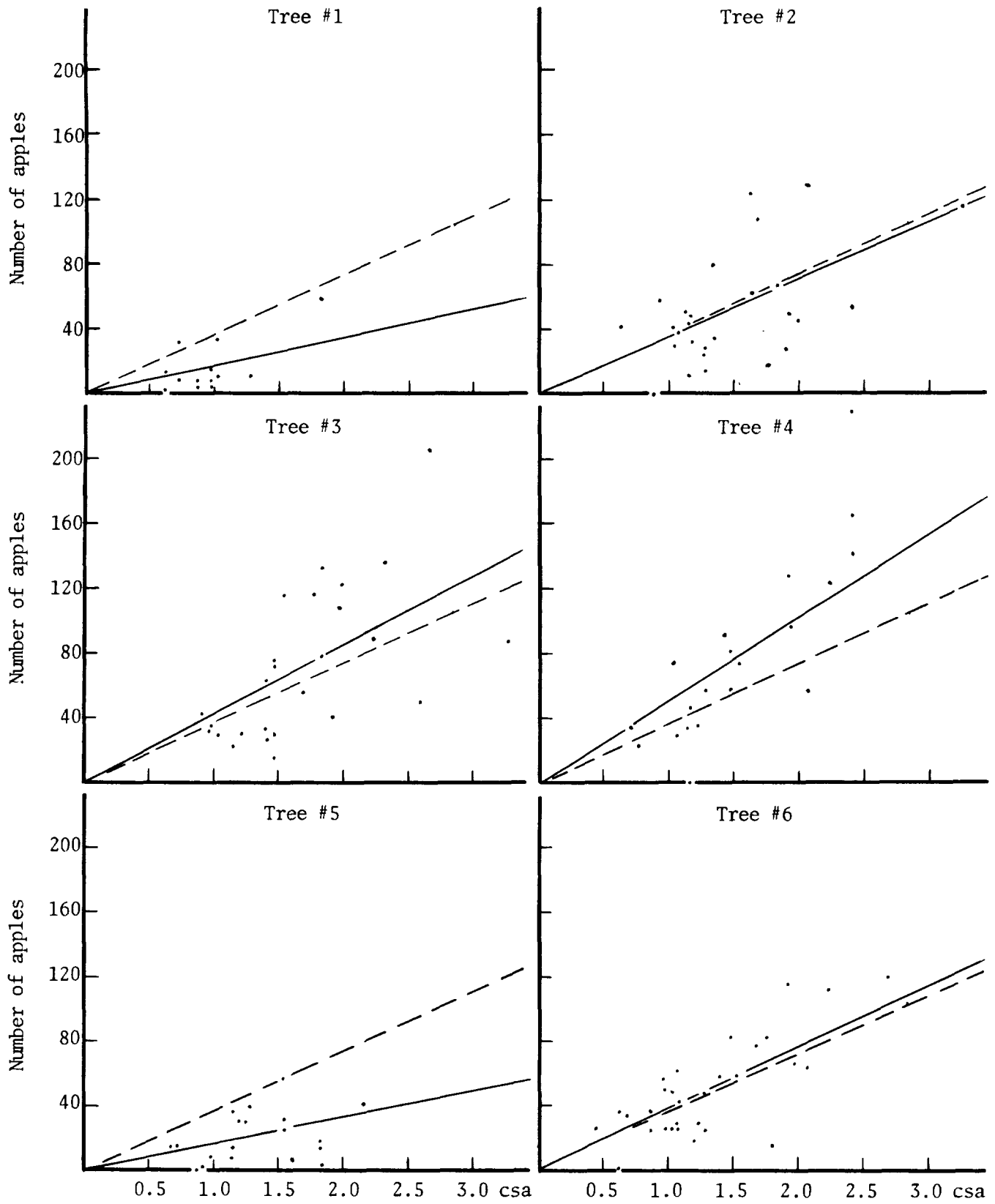


Figure 2.3--Dot charts and ratio lines by trees

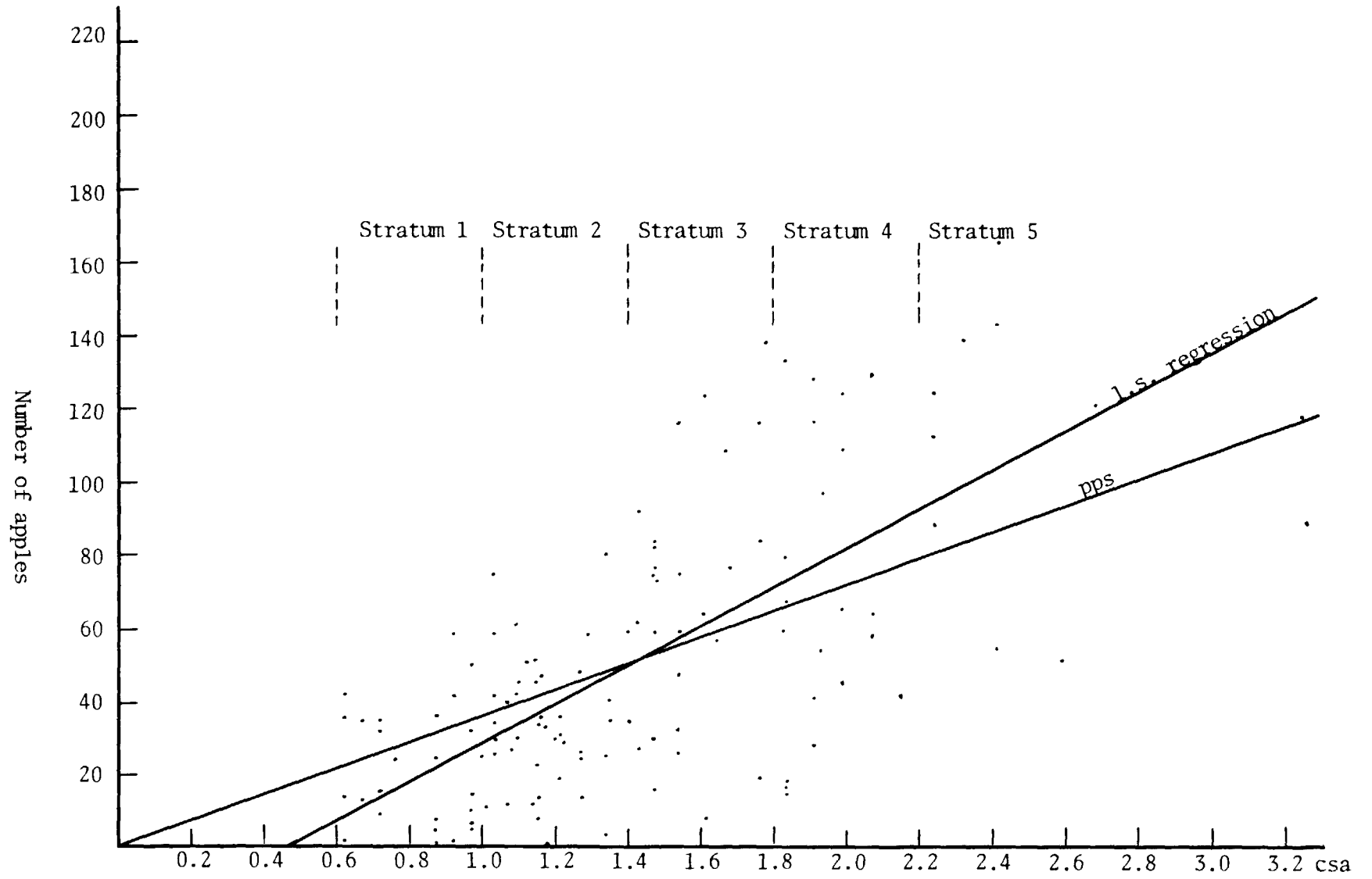


Figure 2.4--Size-of-branch strata, least squares regression line, and line for pps.

CHAPTER III
RANDOM-PATH SAMPLING OF FRUIT TREES

3.1 INTRODUCTION

The methods discussed in Chapter II required a map of each tree to be sampled. A map of a tree provides a good sampling frame, but drawing a map and measuring the csa's of all branches is too time consuming. In the research for practical ways of probability sampling, photographs of trees taken when the trees had no leaves have been studied for possible use as sampling frames, including the estimation of branch sizes for sampling with pps. Photography has also been considered, in the context of double sampling, as a means of counting and estimating the number of fruit on the tree.

In this chapter the random-path method proposed by Jessen^{6/} for sampling fruit on a tree will be illustrated using one of the six apple trees in the analysis in Chapter II. Two random-path methods will be compared with two methods that were discussed in Chapter II. The comparisons will be made as though only one terminal branch from a tree is to be selected and used to estimate the total number of fruit on the tree.

^{6/} Jessen, Raymond J., Determining the Fruit Count on a Tree by Randomized Branch Sampling, Biometrics, March 1955.

3.2 FOUR METHODS OF SAMPLING A TREE

The four sampling methods and estimators, as described in this section, include only apples that are on terminal branches. A small proportion of the apples are not on terminal branches. Methods of including these apples will be discussed later.

(1) The first method is included primarily as a base for comparison. It is the same as Plan 1 discussed in Chapter II. After all terminal branches on a tree have been identified and numbered, one branch is selected at random with equal probability. Apples on the sample branch are then counted. The estimator is Ny_i where N is the number of branches on the tree and y_i is the number of apples on the sample branch. Since y_i refers to a sample value, one would expect i to be the index for branches in a sample. But, we are considering a sample of only one branch and it is convenient to let i be the index to branches in the population. Thus, if the 5th branch in the population, Y_1, Y_2, \dots, Y_N , happens to be selected, $y_i = Y_5$. The first method will be referred to as DS-EP, which means direct selection from a list of all branches with equal probabilities.

(2) The second method is a random-path technique. Beginning from the bottom of the tree, the primary branches are all identified and one of the primary branches is selected at random with equal probabilities. The selected primary branch is then examined to identify all second-stage branches from it. Then, one second-stage branch is selected at random with equal probabilities. The process

is discontinued when a terminal branch has been selected. The estimator is $\frac{y_i}{p_i}$ where p_i is the probability of selecting the particular terminal branch that happens to be selected. As a short title for this method RP-EP will be used where RP represents random path and EP means equal probability of selection at each stage of branching.

(3) Like the first method, the third requires a complete identification of all terminal branches prior to selection. The csa (cross sectional area) of each terminal branch is measured and one branch is selected with pps, probability proportional to csa. The estimator is $X \frac{y_i}{x_i}$, where x_i is the csa of the selected branch and X is the sum of the csa's of all terminal branches on the tree. DS-PPS is the short title for this method, which is the same as plan 2 in Chapter II.

(4) The fourth method is a random-path method which differs from method two in the probability of selection. At each stage of branching the csa's of the branches at that stage are measured and one branch is selected with pps. The estimator, $\frac{y_i}{p_i}$, is like the estimator for the second method but the values of p_i are different. This method is titled RP-PPS.

3.3 BRANCH IDENTIFICATION AND DESCRIPTION OF DATA

Data for tree No. 3, which was represented in Figure 2.1, are presented in Table 3.1 in a way that shows the stage of branching. There were only three primary branches. Their csa's

11.60, 13.45, and 12.84, are presented in the column titled csa under 1st stage. The sum of these csa's is 37.89. Thus, if a primary branch is selected with pps, the first primary branch would have a selection probability equal to $\frac{11.60}{37.89}$. For further illustration of the recording system, notice that the second digit of the identification number shows four second-stage branches from the second primary branch. The csa's of these four branches and their sum are recorded under 2nd stage. This scheme of branch identification and recording is continued until a terminal branch is reached. When this occurs, the number of apples on a terminal branch is recorded to the right of its csa. Thus, Table 3.1 shows, for example, that branch 2-3 was a terminal branch with a csa equal to 1.99 square inches and that it had 124 apples on it. The numbers in parenthesis are numbers of "path" apples which will be discussed later.

Terminal branches were defined as branches having a csa between $\frac{3}{4}$ and 2 square inches. Adherence to exact size is not possible. For example, the first terminal branch 1-1-1 has a csa equal to 2.68 and is large enough so an additional stage of branching was probably considered. If from 1-1-1 there were two branches of about equal size, those two branches would have been terminal branches. Probably 1-1-1 divided into several branches that were too small to be considered as terminal branches. As another case, suppose at the last stage of branching there is a branch with a csa of 1.5 square inches which is dying and clearly has no fruit. This branch could be shown on the map but marked for exclusion and not counted as a branch for sampling purposes.

Along a path from the base of a tree to a terminal branch there are some branches which are much too small to qualify as terminal branches. Fruit on small branches along a path to a terminal branch have been called path fruit and must be accounted for in some way. For example, on the path from the base of 1-2 to the bases of 1-2-1 and 1-2-2 there were three apples. These three apples are recorded in Figure 2.1 and in Table 3.1 next to the csa of branch 1-2. The counts of apples along the paths are shown in parenthesis in Table 3.1 to distinguish such apples from apples on the terminal branches. There are various ways of dealing with the path fruit; but, first let us examine the probability of selecting any given terminal branch with regard to each of the four methods.

3.4 PROBABILITY OF SELECTION AND ESTIMATION

With the DS-EP method each one of the 26 terminal branches has a selection probability equal to $\frac{1}{26}$. With DS-PPS the i^{th} terminal branch has a probability of selection equal to $\frac{X_i}{X}$ where X_i is its csa and $X = \sum X_i$. Calculating the probabilities for the random-path methods is more involved. For example, consider terminal branch 1-2-1-2 and RP-EP. In Table 3.1 notice that the numbers of branches at each stage on the path to terminal branch 1-2-1-2 are 3, 5, 2, and 2. Thus, the probability of selecting branch 1-2-1-2 is $(\frac{1}{3}) (\frac{1}{5}) (\frac{1}{2}) (\frac{1}{2}) = \frac{1}{60}$, which is the product of the probabilities of selection at the four stages. With RP-PPS the product of corresponding probabilities

at the four stages is $(\frac{11.60}{37.90}) (\frac{5.61}{14.94}) (\frac{4.13}{5.96}) (\frac{2.32}{3.80}) = .04862$

An estimator for each of the four methods was presented above. However, all of the four estimators can be written in the same form,

$$\hat{Y}_i = \frac{y_i}{p_i} \quad (3.1)$$

where \hat{Y}_i is the estimator and $i = 1, 2, \dots, N$ is the index to terminal branches on the tree. If the i^{th} branch happens to be selected, then $\frac{y_i}{p_i}$ is the estimate of the total number of apples on the tree (except that path apples are not included) where y_i is the number of apples on the i^{th} terminal branch and p_i is the probability of selecting it. The value of p_i depends on the method of sampling. In fact there are four sets of probabilities, one for each method. These four sets of values are presented in Table 3.2 in the columns headed $P_1, P_2, P_3,$ and P_4 . The columns headed $\hat{Y}_1, \hat{Y}_2, \hat{Y}_3,$ and \hat{Y}_4 contain estimates of the total number of apples on the tree depending upon the terminal branch that happens to be selected. A discussion of these estimates follows.

Exercise 3.1 Refer to Table 3.1 and for each of the four sampling methods compute the selection probabilities for terminal branches 2-3 and 3-2-4. Compare your answers with the probabilities presented in Table 3.2.

To include the path apples there are at least two possibilities that might be considered with regard to the DS-EP and

DS-PPS methods: (1) Count all path apples and add the count to the estimate of the total number of apples on terminal branches that is obtained from a sample of terminal branches; (2) Define sampling units that are sections of path between the base of the tree and the terminal branches. Then select a sample of such sections to estimate the path fruit.

With the random-path methods, it is necessary to count the apples on each section of the path along the path to a terminal branch. Also, it is necessary to determine the probability that each section of the path had of being in the sample.

Since the RP-PPS method is of primary interest, it will be used to illustrate how the path fruit can be accounted for in the estimation process. Consider the three apples (see Table 3.1) on the path section 1-2 which is the section between the base of 1-2 and the third stage branches. To find the probability of these three being in the sample, consider repeated application of a random-path sampling method. These three apples will be in the sample whenever this path section is traversed. Therefore, under the RP-PPS method, the probability of this path section being in the sample is

$\left(\frac{11.60}{37.89}\right) \left(\frac{5.61}{14.94}\right) = .1150$ which gives $\frac{3}{.1150} = 26.1$ apples to be included in the estimate whenever this path section is traversed.

It is important to observe that a random path always ends with one and only one terminal branch. There are three terminal branches, 1-2-1-1, 1-2-1-2, and 1-2-2 that are connected

to the path section 1-2, and 26.1 would be included in the estimate that is made from the selected terminal branch that follows path section 1-2. There are no path apples other than the three that have been mentioned between the base of the tree and the three terminal branches that follow path section 1-2. Therefore, the estimated total number of apples in the event any one of the three terminal branches is selected would be:

<u>Terminal Branch</u>	<u>Estimate</u>
1-2-1-1	$\frac{3}{.1150} + \frac{73}{.03103} = 2379$
1-2-1-2	$\frac{3}{.1150} + \frac{138}{.04864} = 2863$
1-2-2	$\frac{3}{.1150} + \frac{133}{.03530} = 3794$

With the application of either random-path method, and assuming path fruit are recorded for each path section that is traversed, an estimator that includes path fruit can be written in generalized form. It appears to be complicated, but an illustration follows that should help clarify it. The estimator is:

$$\hat{Y}_i = \frac{y_{oi}}{p_{oi}} + \dots + \frac{y_{ki}}{(p_{oi}) \dots (p_{ki})} + \dots + \frac{y_{ti}}{(p_{oi}) \dots (p_{ti})} \quad (3.2)$$

where $i = 1, 2, \dots, N$ is an index of the terminal branches
 $k = 0, 1, \dots, t$ is an index of the path sections of
the path to the i^{th} terminal branch (t is not
constant, it depends on i),

y_{ki} = the number of path fruit on the k^{th} path section of the path from the base of the tree to the i^{th} terminal branch,

p_{ki} = the conditional probability of selecting the k^{th} path section of the path to the i^{th} terminal branch, given that the preceding path section has been selected.

When $k = 0$, the path section referred to is the part of the tree between ground level and the bases of the primary or first stage branches. Given that the tree is in the sample, $p_{0i} = 1$ which means that this path section is a part of the path to every terminal branch. Generally, y_{0i} , the number of fruit on this section of the tree, will be zero. When $k = t$, the k^{th} path section becomes a terminal branch, thus y_{ti} is the number of apples on the i^{th} terminal branch, and p_{ti} is the conditional probability of selecting the i^{th} terminal branch given that the path section that it is connected to has already been selected.

Suppose application of the RP-PPS method leads to terminal branch 1-2-1-1. In this case, $k = 0, 1, 2, 3, 4$ and the values of y_{ki} and p_{ki} are:

<u>Path section</u>	<u>No. of apples on path section, y_{ki}</u>	<u>Conditional probability, p_{ki}</u>
0	0	1
1	0	$\frac{11.60}{37.89} = .3061$
2	3	$\frac{5.61}{14.94} = .3755$
3	0	$\frac{4.13}{5.96} = .6930$
4	73	$\frac{1.48}{3.80} = .3895$

Substituting these values of y_{ki} and p_{ki} in the estimator, (3.2), gives:

$$\begin{aligned} & \frac{(0)}{(1)} + \frac{(0)}{(1)(.3061)} + \frac{(3)}{(1)(.3061)(.3755)} + \frac{(0)}{(1)(.3061)(.3755)(.6930)} \\ & + \frac{(73)}{(1)(.3061)(.3755)(.6930)(.3895)} = 2379 \end{aligned}$$

Exercise 13.2 For the RP-EP and RP-PPS methods use the estimator (3.2) to obtain estimates corresponding to terminal branches 3-1-2, 3-1-4-1, and 3-3. Your results should agree with the estimates presented in Table 3.2.

There is an alternative view of the above method of including the path fruit which leads to the same answers. The idea is to prorate the path fruit to the terminal branches that follow the sections of the path where the path fruit are found. The prorating is done according to the probabilities of selection. Under the RP-EP method the three apples on the path section 1-2 would be prorated as follows:

<u>Terminal branch</u>	<u>Prorated amount</u>
1-2-1-1	$(\frac{1}{2})(\frac{1}{2})(3) = .75$
1-2-1-2	$(\frac{1}{2})(\frac{1}{2})(3) = .75$
1-2-2	$(\frac{1}{2})(3) = \underline{1.50}$
	Total = 3.00

Notice that $(\frac{1}{2})(\frac{1}{2})$, $(\frac{1}{2})(\frac{1}{2})$, and $(\frac{1}{2})$ are the conditional probabilities of selecting one of the three terminal branches, given that the path section 1-2 has already been selected. The conditional probabilities add to 1 which verifies that the method of prorating accounts for all of the path fruit.

If 1-2-1-1, for example, is the selected terminal branch, .75 is added to 73, the number of apples on 1-2-1-1. The estimate of the total number of apples on the tree is then obtained by dividing 73.75 by the probability of selecting 1-2-1-1 which is $(\frac{1}{3})(\frac{1}{5})(\frac{1}{2})(\frac{1}{2}) = \frac{1}{60}$. Thus, $(60)(73.75) = 4425$. The branch total, 73.75, (including the prorated amount) appears in Table 3.1 in the column titled EP, and the expanded total, 4425, appears in Table 3.2 in the column titled \hat{Y}_2 .