types of selection bias frequently encountered in surveying private residences.

COSTS

One of the other major advantages claimed for this technique is the cost advantage over more traditional techniques. Since much of the cost of such a survey is borne by the cooperating employer and workers, the cost to COG was very low. The average employer distributed 35 questionnaires to employees, who on the average mailed back 11 completed forms. Because many of these employers were clustered within walking distance of each other, transportation costs were less than $0.50/site. More important, interviewer productivity was high: The initial employer contact could be completed in an hour, and frequently two businesses per hour could be visited. The salary cost per interview was about $1.25, an order of magnitude lower than the cost of obtaining the same data through personal interview.

SUMMARY

This paper has reported the experience from two large travel surveys of downtown workers conducted through the cooperation of employers. The results indicate that this technique has some major advantages over more traditional home-based interviews. Small businesses and retailers showed a lower rate of cooperation than other firms if there was no follow-up, but they were almost as cooperative as other businesses when they were told that a call-back visit would be made to pick up completed questionnaires. Once employers received the questionnaires, the response rate of workers in small businesses was actually much higher than that in larger firms. An important measure that seems to increase the response rate is to make the employer responsible for collecting completed questionnaires. This approach was not taken in the before survey because of the possibility that respondents would fear the disclosure of confidential information to their employer. However, use of this technique in the after survey caused no major problems. A similar survey conducted in the San Francisco area (which did not collect as much confidential household data) produced an excellent response rate of 58 percent by collecting the questionnaires through the employers (3). Finally, because much of the cost of this type of survey is absorbed by the employer, the survey cost to the sponsor is relatively low.

ACKNOWLEDGMENT

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Design of Small-Sample Home-Interview Travel Surveys

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Procedures for use in designing small-sample home-interview travel surveys are described. The following steps are addressed: (a) Decide on the purpose of the survey, (b) decide which variables should be measured to fulfill the purpose, (c) decide whether a home-interview travel survey can adequately measure the variables in question, (d) determine the coefficients of variation of the variables in question, (e) decide on a level of accuracy and a confidence limit, and (f) based on steps d and e, compute the sample size. Methods for using stratified sample frames are also discussed. The techniques are illustrated by using composite data from several urban areas. These data indicate that travel demand models can be developed from a survey of less than 1000 households.

The first step in any data collection is to decide on the purpose for collecting the data. If this decision is not made with the utmost care, there is a real danger that the survey will fail to produce the desired results. In the past, most origin-destination surveys of the home-interview type were conducted to replicate travel patterns in an urban area. Great care was taken to ensure that the survey instrument—i.e., the household questionnaire—was designed to extract just the right data. However, the sample sizes were not usually based on their ability to produce desired statistics within a specified accuracy. Usually 1 out of 10 or 1 out of 20 households was interviewed, on the basis of past experience or judgment, to duplicate travel patterns in the area (1). As a result, large sums of money were spent, and a large number of data were collected. The relations developed from these data have resulted in increased knowledge about the structure and interdependence of variables appropriate for travel demand forecasting. This increased knowledge should allow the development of procedures for determining sample-size requirements by statistical means.

The purpose of this paper is twofold: (a) to provide the transportation planner with a procedure that uses local data to estimate the required sample size for conducting a home-interview origin-destination (O-D) survey and (b) to provide the transportation planner whose local data are limited with typical data needed to determine sample sizes. These procedures are based on the sample sizes required to calibrate travel demand models rather than on sample sizes required to duplicate travel patterns. Therefore, in following the procedures described here the transportation planner will usually find that the sample size required for an O-D survey is smaller than conventionally thought. Thus, application of these procedures is likely to result in more cost-effective data collection and an overall savings of funds because fewer data need to be collected.

The methods described in this paper cannot be used to determine sample sizes for all kinds of transportation surveys, however. Only O-D surveys of the home-interview type are covered. Before consulting these methods, therefore, the planner must first decide whether such a survey is necessary. In general, a new O-D survey is needed if either of the following conditions exists:

1. There has never been an O-D survey in the area and models cannot be successfully borrowed from another area.
2. The previous O-D survey has been used to update old, unusable models, and the updated models yield unsatisfactory results. Normally, this occurs only when the previously collected data are fraught with errors or omissions or major land-use and growth changes have occurred that have significantly altered travel behavior in the area.

Statistically, sample sizes can be computed if the following information is known: (a) the variable to be estimated; (b) the coefficient of variation or, alternatively, the mean and standard deviation of the variable; and (c) the desired accuracy level and confidence limits. Each of these three components has often been ignored in the past.

The first component is basic. Before any survey is begun, one should know what the survey is going to measure. However, this requirement has often been forgotten. Most O-D surveys in the past were ostensibly designed to reproduce "travel patterns". Travel patterns may mean desire lines or entries in an O-D table. Not only is the definition of travel patterns vague but, with either definition, travel patterns are also impossible to measure with any reasonable degree of accuracy by using any reasonably sized O-D survey.

The second component is knowledge of the coefficient of variation (CV) of the variable being measured. When earlier surveys were taken, there was no such knowledge. Now, however, CVs of all kinds of variables related to transportation planning can be derived from past surveys in the same or similar areas. The procedures outlined in this paper assume such knowledge. If these data are unavailable in a particular area, the CVs shown in the examples in this paper can be used.

When the value of a particular variable is to be measured by a survey, the desired level of accuracy and confidence limit should be selected beforehand. An accuracy level is the percentage of sampling error that is acceptable to the analyst. For example, it may be decided that enough samples should be collected to estimate the average household trip rate to within ±10 percent. That is, if a trip rate of 8.0 trips/household is measured, the analyst wants to be reasonably sure that the true trip rate is between 7.2 and 8.8. Just how reasonably sure the analyst can be is determined by the confidence limit. Suppose a confidence limit of 90 percent is specified. The analyst would then be 90 percent sure that the true trip rate actually was between 7.2 and 8.8.

Any sample size can be made arbitrarily large by specifying a strict level of accuracy and a high confidence limit. Conversely, any sample can be made arbitrarily small by specifying a loose level of accuracy and a low confidence limit. Thus, substantial judgment is required in selecting the level of accuracy and the confidence limit. This is the art of statistically based sample-size determination. The important point is that selection of these figures quantifies the sampling accuracy of the survey.

Once the three elements of statistically based sample design have been determined, the sample size can be computed. The remainder of this paper is devoted to determining these three elements for each of the four steps in the traditional process of travel demand forecasting: trip generation, trip distribution, mode choice, and traffic assignment. The numbers used are composites taken from data collected in several urban areas. If the reader has no similar data for his or her area, these composites can be used.

In computing sample sizes, the formula used is

$$n = C^2Z^2/E^2 \qquad (1)$$

where

C = coefficient of variation,
E = accuracy level expressed as a proportion rather than a percentage,
n = number of samples, and
Z = normal variate.

The normal variate depends on the confidence limit selected. Knowing the confidence limit, the analyst can find the value of Z by using standard statistical tables. Equation 1 will be referred to throughout this paper as the sampling equation.

TRIP GENERATION

Trip generation is dealt with in two phases: trip production and trip attraction. Forecasts of total trip attractions are adjusted to agree with trip productions because the latter are considered more accurate. Therefore, sample sizes for creating accurate estimates of trip-production parameters are discussed here.

Since trip production occurs, by definition, at the household level, the appropriate variable to measure is trips per household. To measure trips per household to a desired level of accuracy, the CV of the variable must be known. Usually, the CV can be computed from previously collected local data. If local data are unavailable, a CV from a similar area, or an overall average of CVs from other areas, can be borrowed. To aid the planner who has no local data to use in computing a CV, an average CV from several areas is used here. A generalized sample size is then computed to illustrate the procedures of sample-size calculation. The table below gives some of the CVs that have been reported or computed:

CV	Variable	Source
0.28	For single-family homes only	Arizona Department of Transportation (2)
0.87	For all households	Nationwide Personal Transportation Survey (3)

CV	Variable	Source
0.86	For all households	Southwestern Pennsylvania Regional Planning Commission
1.07	For all households	Manchester, New Hampshire, 1964 O-D survey
1.05	For all households	Baltimore 1962 O-D survey

As can be seen, the computation of a generalized sample size is confounded by the variety of CVs available (2, 3). Except for the first CV, which is for single-family homes, all the CVs are close to 1. So, from this point on, sample sizes needed to compute trip rates will be based on a CV of 1.

The next step in computing a sample size to measure trip production is to decide on a level of accuracy and a confidence limit. This is the most difficult step in the process. These two parameters must be specified subjectively. To do this, the precise meaning and effect of each term need to be fully understood.

Level of accuracy has already been described and needs no further amplification. If a confidence limit of 50 percent is specified, half of the samples drawn will yield a statistic within the desired level of accuracy. This is the same confidence that would be generated by flipping a coin. Therefore, a stricter confidence limit is usually set. Confidence limits of 90, 95, and 99 percent are most often used. At a 90 percent confidence limit, 9 out of 10 sample groups will yield statistics within the desired level of accuracy; at 95 percent, the ratio is 19 out of 20; and at 99 percent, the ratio is 99 out of 100. Since sample size increases exponentially as the 100 percent confidence limit is approached, very strict confidence limits are seldom used; they are simply not worth the extra effort. For illustration, the 90 percent confidence limit is used in this paper for all sample-size calculations.

In computing a trip rate, high levels of accuracy should be set because the entire model sequence is driven by the number of trips generated. Accurate trip-generation rates do not, however, guarantee the production of a good set of models. For purposes of analysis in this paper, an accuracy level of 5 percent was chosen. Coupling this figure with a 90 percent confidence limit and a CV of 1, the sample size is computed by using Equation 1, where $C = 1.00$, Z (which depends on confidence limit α) $= 1.645$ (for $\alpha = 90$ percent), and E = accuracy level as proportion $= 0.05$, or $n = (1.0)^2 (1.645)^2/(0.05)^2 = 1084$. So about 1000 samples will produce a trip-rate estimate to a tolerance of ±5 percent 90 percent of the time.

This procedure is fine if only a current estimate of the total number of trips per day in a given area is needed. However, a forecast of travel is usually desired. Therefore, the base-year trip rate is usually related to some of the other variables collected in the survey. These variables most commonly include automobile ownership, household income, and family size. If trip rates are cross-classified by automobile ownership and income, as in the table below, an estimate of each trip rate is desired:

Income	Automobiles Owned: 0	1	≥2
Low	1.20	4.42	8.50
Medium	2.62	6.57	9.69
High	2.97	7.79	11.21

Each trip rate, however, does not have to conform to the same strict level of accuracy as the overall trip rate. Instead, a statistical technique for calculating sample sizes based on a stratified sample (in this case, stratified by income and automobile ownership) can be used. To use this technique, an overall level of accuracy is first selected. In this case, as before, it is assumed that the overall trip rate must be known to within 5 percent.

The next step is to compute a set of modified CVs, one for each cell. These CVs are modified in that they are computed by dividing each cell standard deviation not by each cell mean but by the overall mean. In conducting the background research for this paper, it was found that the set of modified CVs for trip rates cross-classified by income and automobile ownership were very similar for each urbanized area tested. A matrix of the average modified CVs computed is given below:

Income	Automobiles Owned: 0	1	≥2
Low	0.31	0.72	1.02
Medium	0.40	0.92	1.26
High	0.45	0.99	1.24

After the matrix of modified CVs is obtained, an estimate of cell frequencies is needed. This requirement is based on the idea that cells that contain few households (such as the high-income, zero-automobiles cell) will not require estimates as stringent as those for more frequent cells. A realistic example of cell frequencies (i.e., an average of several areas) is given below:

Income	Automobiles Owned: 0	1	≥2
Low	0.124	0.124	0.023
Medium	0.026	0.266	0.125
High	0.010	0.150	0.152

Use of Equation 1 requires a single CV, designated by C in the formula. In this case, however, many coefficients of variation are available. To get a single measure, each modified CV is multiplied by the corresponding cell frequency. The sum of the products is then the measure desired.

Thus, $C^* = \Sigma f_i C_i$, where i = cell index, f_i = frequency of cell i, and C_i = modified CV for cell i. C^* is then used in the sampling equation: $n = C^{*2}Z^2/E^2$, or $n = F C^{*2}$, where $F = (Z/E)^2$. The table below gives values of F:

Level of Accuracy (%)	Sample-Size Factors by Confidence Limit: 99 Percent	95 Percent	90 Percent	68 Percent
1	66 306	38 416	27 060	10 000
5	2 652	1 537	1 082	400
10	663.1	384.2	270.6	100
25	106.1	61.5	43.3	16

The application of these procedures is illustrated by the following step-by-step example, in which the data given in the second, third, and fourth tables above are used:

1. Enter the modified CVs (C_i) for each cell of the cross-classification matrix into column 3 of the worksheet given in Table 1. This worksheet is designed for analysis of a nine-cell matrix; for larger matrices, a larger worksheet would be used. The cell number that has the largest CV should be entered in the "critical cell" line.

Table 1. Worksheet for computing sample size.

Cell	Standard Deviation	Modified CV(C_i)	Frequency (f_i)	Factor (f_iC_i)[a]	Weight (W_i)[b]	Optimal Allocation[c]	Expected Frequency[d]	Full Random Sample[e]
1		0.31	0.124	0.038	0.042	37	110	154
2		0.72	0.124	0.089	0.098	87	110	154
3		1.02	0.023	0.023	0.025	23	20	28
4		0.40	0.026	0.010	0.011	10	23	32
5		0.92	0.266	0.246	0.271	240	236	329
6		1.26	0.125	0.158	0.175	155	111	155
7		0.45	0.010	0.005	0.006	5	9	12
8		0.99	0.150	0.149	0.165	146	133	186
9		1.24	0.152	0.188	0.208	184	135	189
Sum				0.905	1.000	887	887	1239
Critical cell		6						

[a]Column 3 × column 4. [b]Column 5/Σf_iC_i. [c](Column 5)xn. [d](Column 4)xn. [e](Column 4)xe.

2. Enter the cell frequencies (f_i) in column 4.

3. Multiply each CV in column 2 by the corresponding frequency in column 3. Record each product in column 5. Sum the entries in column 5, and record the sum at the bottom of the column. This sum is C*.

4. Choose a desired level of accuracy and confidence limit. In this case, ±5 percent level of accuracy and a confidence limit of 90 percent have been chosen.

5. Find the sample-size factor F (from the table in the text above) given the accuracy level and confidence limit. In this case, F = 1082.

6. Multiply F by the square of C*. The result is the sample size, i.e., $n = FC^{*2} = (1082)\,(0.905)^2 = 887$.

The resulting sample size of 887 is smaller than the 1084 computed for the simple, unclassified sample. There is a price that must be paid for this reduction, however. The sample size of 887 is for an optimally allocated sample; that is, the sample units must be selected in such a way that each cell in the cross-classification matrix contains an optimal number of samples. To determine this allocation, first divide each f_iC_i by the sum Σf_iC_i. The resulting weights W_i, when multiplied by the total number of samples (887 in this case), will yield the optimal allocation of samples. How to compute the optimal allocation of the sample and analyze the results is shown in the following continuation of the step-by-step example:

7. Divide each f_iC_i by the sum of the f_iC_i entries. Record the answers in column 6 of the worksheet, labeled W_i. For example, $W = (f_1C_1/\Sigma f_iC_i) = (0.038/0.905) = 0.042$. As a check, the sum of the W_i's should be 1.0.

8. Multiply each W_i by 887 (total samples from step 6), and round it off to the nearest integer. Record each product in column 7 of the worksheet. This is the number of samples required for each cell. As a check, the sum of the cell samples should be equal to the total number of samples (in this case, 887).

9. Multiply each f_i (see column 4 of the worksheet in Table 1) by the total sample size from step 6 above (in this case, 887). Record each product in column 7. This is the number of households that could be expected to fall in the various categories if a random sample of 887 households were drawn. So, if 887 households are drawn at random, 135 of them will be expected to fall in cell 9. But 184 samples are needed in this cell (see column 7 of the worksheet). Other cells will also be short of samples if a random sample of 887 is drawn.

10. The cell in which the shortfall of samples is most critical needs to be identified. In column 3 of Table 1, cell 6 was found to have the largest modified CV (see step 4). This is the critical cell.

11. The next step is to determine how much of a shortfall exists in the critical cell. To find out, divide the samples required (column 7) by the expected frequency (column 8) for the critical cell. In this case, the shortfall ratio is 155/111 = 1.396. Thus, the expected frequency for cell 6 falls short of the required number of samples by 39.6 percent.

12. Multiply each expected frequency in column 8 of the worksheet by the shortfall ratio found in step 11 above. Record the results for each cell in column 9. Sum the results. This sum represents the total number of random samples required to obtain sufficient samples in the critical cell. In this case, 1239 samples are required.

The number of samples required, computed by the above steps, is somewhat misleading. Although 1239 random samples are needed to produce the correct number of households in the critical cell, all other cells will have more samples than are needed to produce the overall trip rate within the desired accuracy and confidence limits. For example, 330 of the 1239 samples will fall in cell 5, but only 240 samples are required in that cell.

This excess can be handled in two ways. The first way is to conduct interviews at all 1239 households. Although more than the minimal data are collected, the data are at least sufficient to produce the desired statistic within the desired confidence and accuracy limits. But conducting complete interviews at all 1239 households may not be cost effective. A multistage sample design may be a better choice.

A multistage sample design consists of the following stages:

1. Collect a small amount of information from a large sample.

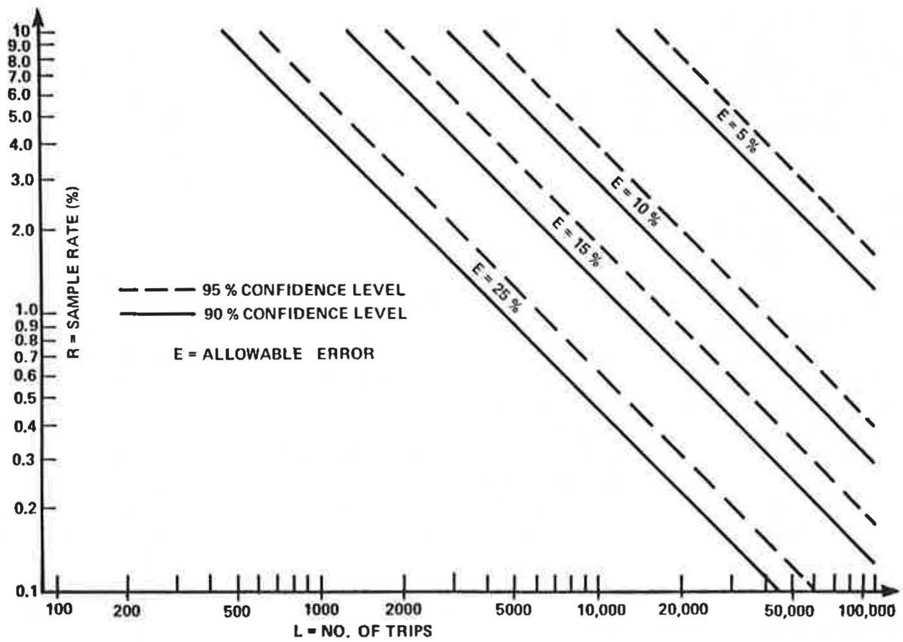
2. Stratify the households interviewed in stage 1 by the variables collected.

3. Identify a subset of households for an in-depth-interview stage based on the stratification made in stage 2.

In this case, 1239 first-stage interviews would be conducted. In each of the first-stage interviews, only enough information would be collected to assign the household to an income versus automobile ownership cross-classification matrix. After all 1239 households were so assigned, 887 of them would be selected for the in-depth interview. The number of households to be reinterviewed in each cell would be determined by the optimal allocation of households shown in column 7 of Table 1.

Alternatively, a multistage sample design can be performed by using a branched questionnaire. The interviewer asks enough questions to determine the category to which the household belongs. If the quota established

Figure 1. Sample rates for trip distribution.



for households in that category has been filled, the interviewer stops there and goes on to the next sample.

To determine which alternative—the full set of interviews or the multistage design—is the more cost effective, the following continuation of the step-by-step procedure is used:

13. The shortfall ratio computed in step 11 can be thought of as an expansion factor e inasmuch as it was used to expand the original sample size. The cost-effectiveness of the multistage procedure depends on e according to the following formula: $r = [e/(e - 1)]$ $[1.396/(1.396 - 1)] = 3.53$, where r is the cost-effectiveness ratio.

14. Divide the actual cost of an in-depth survey by the actual cost of a first-stage survey to yield the survey cost ratio R. In this case, assume a first-stage survey costs $10 and an in-depth survey costs $33. Then, $R = 33/10 = 3.3$.

15. If R is greater than the cost-effectiveness ratio r, conduct the survey according to a multistage sample design. Since in this case $R < r$, a multistage sample design would not be used. Instead, in-depth interviews would be conducted at all 1239 households. It should be noted, however, that the difference between R and r is very small in this case. Since the procedure for computing R and r used estimated figures, the analyst may, in this case, want to consider other, more subjective criteria before making a decision on which sampling method to use.

TRIP DISTRIBUTION

One way to approach sample-size determination for estimating patterns of trip distribution is to presume that the number of trips in each cell of the O-D matrix is to be determined within an acceptable degree of precision. Figure 1 shows the sample size required in making such an estimation. In the graph, L represents the number of trips expected for a given interchange. Thus, if an interchange that is expected to have a volume of about 1000 trips is to be measured to within 25 percent at 90 percent confidence, an R of 4.3 percent is required. The sampling rate is based on randomly selected trips rather than randomly selected households. If households are used as the primary sampling units, trip clusters will be measured; therefore, some of the variance will not be accounted for, and the sample size required will be greater.

The preceding argument shows that, even for very large interchange volumes, a high sampling rate is required to produce acceptable volume estimates. For ordinary volumes on the order of 20-30 per cell, the required sampling rate approaches 100 percent. It is not feasible, therefore, to produce an accurate O-D trip table from any reasonably sized home-interview survey. Even the large surveys conducted in the past had no hope of reproducing interchange volumes at the zonal level within a reasonable degree of accuracy.

How, then, are trip interchanges to be measured? Since they cannot be measured directly, they must be simulated. The most commonly used method of simulating travel patterns is the gravity model. Since calibration of the gravity model depends on the trip-length frequency distribution (TLFD), an accurate measurement of TLFD should provide the tool required to produce a reasonably accurate O-D trip table.

The problem with measuring a TLFD to within a given level of accuracy is in trying to designate one specific variable to measure. A TLFD is, by definition, a distribution of numbers rather than one single number. If, however, one single number can be found from which the entire TLFD can be derived, the task of sample-size determination will be much easier.

Fortunately, TLFDs can be derived from a single measure. Pearson and others (4) have shown that reasonable estimates of TLFDs, by trip purpose, can be derived from the mean trip length for each purpose.

Now that the variable to be measured is known, the coefficient of variation must be calculated. In their research, Pearson and others (4) created a standard TLFD for each trip purpose. In the process, they also created an implied CV of trip length for each trip purpose.

Given that the mean trip length, by trip purpose, is the variable to measure and given the CVs for each purpose, the only remaining task before computing the sample size required is to select a level of accuracy and a confidence limit. In keeping with the precedent established for trip generation, 5 percent accuracy at 90 percent confidence is used here for purposes of analysis.

When all three elements of the procedure for determining sample size are identified, the sample size can be determined by using the simple sampling equation, Equation 1. In this case, $Z = 1.645$ and $E = 0.05$; C and the resulting sample sizes are given in the table below:

Trip Purpose	C	Sample Size
Home-based work	0.53	574
Home-based nonwork	0.58	628
Non-home-based	0.63	682

The sample sizes are in trips rather than households. In conducting the background research for this report, it was found that urban households report an average of about 7 trips/day—25 percent being home-based work trips, 50 percent being home-based other trips, and 25 percent being non-home-based trips. By using these assumptions, the number of trips by purpose that would be generated from the 887 households selected to determine trip rates can be computed. The number of trips computed in this way are given below:

Trip Purpose	Trips
Home-based work	1552
Home-based nonwork	3104
Non-home-based	1552
Total	6209

As the numbers given above show, far more trips will be samples than the number necessary to compute a TLFD for each trip purpose. Therefore, if the number of trips per household, or the assumptions about the purpose split of trips, is changed slightly, the sample size will still be sufficient. In addition, sampling households to get a sample of trips introduces a clustering bias that increases the required sample size. Fortunately, this bias is small for computing mean trip length (5). Therefore, the excess samples shown should be more than sufficient to cover the bias.

The above analysis shows that a relatively small sample can be used to calibrate a gravity model. The analysis was based on the estimation, by statistical means, of the same sizes required to compute specific quantities. Other research performed by Ben and others (6) shows empirically that even samples as small as 600 trips can adequately reproduce a trip-length frequency distribution (6).

MODE CHOICE

There are three approaches to estimating the sample sizes required to measure mode choice:

1. Measure the number of automobile trips as well as the number of transit trips to within a few percent.
2. In highway planning, measure the percentage of transit to within a few percentage points to account for the number of automobile trips that the transit system is taking off the road. This measurement must be followed by a measurement of automobile occupancy. This option is particularly useful in smaller urban areas.
3. Calibrate a model for predicting mode-choice percentages under various future transportation options.

Option 1 is difficult with a home-interview survey. In most urban areas, a transit ride is a statistically rare event and therefore hard to measure in a home-interview survey. Data collected in the Nationwide Personal Transportation Survey indicate that the average of transit trips per household was 0.183 and the standard deviation was 0.752. Using these figures, an accuracy level of 5 percent, and a confidence limit of 90 percent yields a sample size of 18 278. Because such large sample sizes are required, home-interview surveys are seldom used to estimate transit demand. Therefore, measurement of transit ridership by a home-interview survey should not be attempted unless (a) because of a very high number of transit trips the CV is much lower than that indicated above or (b) the very large survey required is considered worth the effort.

Pursuing option 2 above requires an estimate of transit share (not transit ridership). For example, suppose it is known that transit captures about 20 percent of all trips. The rest of the trips, or about 80 percent, go by private vehicle (assume that taxis and other paratransit modes carry an insignificant share of the trips). The requirement is to estimate the number of private vehicle trips to within ±5 percent. This requires the range in the estimate of percentage of automobile trips to be 76-84 percent because 4 percent ÷ 80 percent = 0.05. So the percentage of automobile trips must be estimated to within four percentage points. Therefore, the transit share must also be estimated to within four percentage points. Since this is an absolute rather than relative level of accuracy, a slight modification to the sample-size formula is required. The formula to use is

$$n = Z^2S^2/d^2 \qquad (2)$$

where S = standard deviation and d = absolute accuracy level/100 percent.

Applying Equation 2 to the present situation requires an estimation of the standard deviation. This estimate is given by the formula $S = \sqrt{p*(1 - p)}$, where p is the estimated percentage of transit (note that, as p decreases, so does S and, therefore, n). In this case, $S = \sqrt{(0.2) * (0.8)} = 0.4$. In addition, $d = 0.04$ and $Z = 1.645$ (for 90 percent confidence). Therefore, $n = (1.645)^2 (0.04)^2/(0.04)^2 = 271$ trips.

It is apparent that the number of trips to be sampled is far fewer than the number of trips that would be generated, for any given purpose, by the 887 households identified in the trip-generation section. An adequate estimate of transit share can thus be made from a small-sample home-interview survey as long as the percentage of transit trips is relatively low.

The next step in option 2 is to measure automobile occupancy. According to Nationwide Personal Transportation Survey data on the frequency of various automobile-occupancy figures (7), the CV of this variable is 0.69. If $Z = 1.645$ and $E = 0.05$, the required sample size is 725 trips. Again, the 887-household samples for trip production should provide more than enough data.

Thus, it is possible to measure the impact of mode choice on the highway system by using a home-interview survey of reasonable size. Usually, however, a forecast of mode choice under various policy alternatives is required, and this brings us to a discussion of sample-size requirements for option 3.

Usually, a separate mode-choice model is calibrated for each trip purpose. Unlike gravity models, mode-choice models do not have an easily measurable statistic on which they are calibrated. The most popular mode-choice model available is the logit model, which is calibrated on the basis of the maximum likelihood (ML) statistic. Since an ML statistic requires a calibrated logit model for computation, it is not possible to decide beforehand how many samples to collect to estimate the statistic.

Although the required sample size for logit modeling is difficult to derive theoretically, a reasonable range of required samples can be determined from past research in model calibration. In mode-choice modeling with data bases that contain trips (rather than households) as the primary observation unit, about 100-400 samples have been used to calibrate adequate models (8-10). Other logit models have been successfully calibrated by using data from about 500-1300 households (11, 12). Thus, it seems reasonable to be able to produce an adequate model by using the 887 households required to develop production models.

TRAFFIC ASSIGNMENT

The process of traffic assignment starts with a trip table. Since it has been determined that an accurate trip table cannot be produced directly from an O-D survey (unless a sample size approaching 100 percent is used), it follows that route assignments cannot be accurately determined directly from a reasonably sized O-D survey. Further support for this conclusion is available from a set of curves developed by Sosslau and Brokke (13). These curves show that estimating a volume of 1000 vehicles/day to within ±10 percent requires a sample of at least 20 percent of the dwelling units in the area.

Since it is not possible to develop accurate link volumes from a reasonably sized O-D survey of the home-interview type, the sample required to measure variables used in assigning traffic from a simulated trip table needs to be determined. The variables used are, however, system variables—usually travel time. Since traffic assignments are done on the basis of travel times taken from the coded network, data collected in the home interview do not affect the accuracy of traffic assignment as long as an accurate trip table can be synthesized from the data.

CONCLUSIONS

It has been determined that 900-1200 home-interview samples are sufficient to develop a cross-classification model for trip generation based on automobile ownership and income, depending on whether a simple random sample or a multistage sample is taken. It has also been shown that, for the purpose of travel demand forecasting, this sample size is sufficient for calibrating trip-distribution and mode-choice models. For traffic assignment modeling, the size of the home-interview survey is relevant only to the extent that an accurate trip table can be simulated. Computation of the sample sizes required is based on average measures of variability taken from several areas around the country. If variability (CV) is greater in the particular area where these procedures are being applied, a larger sample size will be required; if variability is less, the sample size required will be smaller.

If an O-D survey of the home-interview type is intended for more than or other than the purpose of calibrating travel demand models, other constraints need to be considered. For example, if the overall trip rate is being monitored, about 1100 samples are sufficient. But, if a trip rate for each of several jurisdictions is to be monitored, 1100 samples in each jurisdiction are required.

There are some transportation questions that cannot be cost effectively answered by using an O-D survey of the home-interview type. For example, vehicle kilometers of travel is most effectively measured where it occurs—on the street. Other methods of sample-size determination are applicable in that case. A complete discussion of street sampling to determine vehicle travel is presented elsewhere (14).

Clearly, several things must be done before the procedures in this report can be applied. The planner must first decide on the purpose of the survey and must then determine what variable(s) to measure to respond to that purpose. If it is then determined that the variables in question are amenable to an O-D survey of the home-interview type, the procedures in this report are applicable. But to apply these procedures, the analyst must develop an estimate of the variability in the quantity being measured.

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