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Estimating Confidence Intervals for Transport Mode Share

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ABSTRACT

One of the common statistics used to monitor transport activity is the total travel by a particular method or mode and, for each mode, this share is routinely expressed as a percentage of total personal travel. This article describes a simple model to estimate a confidence interval around this percentage using Monte Carlo simulation. The model takes into account the impact of both measurement errors in counting traffic and daily variations in traffic levels. These confidence intervals can then be used to test reliably for significant changes in mode share. The model can also be used in sensitivity analysis to investigate how sensitive the width of this interval is to changes in the size of the measurement errors and daily fluctuations. A bootstrap technique is then used to validate the Monte Carlo estimated confidence interval.

KEYWORDS: Mode share, confidence intervals, Monte Carlo, bootstrap.

INTRODUCTION

The last 5 to 10 years in United Kingdom transport has seen the establishment of an increasing number of targets against which the performance of the transport system is to be measured. Many of these targets are expressed in precise numerical terms, and sophisticated monitoring regimes are in place to determine the current value of the measure of interest. In some cases, this monitoring can provide complete information about the measure (the population), but more commonly only information on a sample of the measure is possible. Information from the sample is then used to infer the behavior of the population. Statistics tell us that all samples are subject to variation and in judging the value of an indicator (and in particular whether a target has been achieved) some account of this variability is necessary. Therefore, it is important to ensure that the precision of the monitoring regime that estimates the required indicator is compatible with the specified target level for the indicator.

The following section presents the background to the statistic to be modeled in this paper: the percentage of people who travel by a particular mode. The next section describes the Monte Carlo technique used to estimate the confidence interval around this statistic. The following section presents the survey methodology used by the city of Leeds in the United Kingdom to collect the base data. By using the information on how the base data were collected, ranges can be set for likely measurement errors and daily variation, which are detailed in the next two sections. A number of the implicit assumptions that result from this exercise are then highlighted. We next report on the application of the Monte Carlo technique and the issues surrounding the sensitivity analysis and sample size determination. The penultimate section uses the technique of bootstrap estimation to "validate" the Monte Carlo estimates of mode share deviation. The final section provides some suggestions on how the technique can be adapted for other purposes.

MODE SHARE STATISTICS

Local government authorities regularly undertake surveys to measure the volume of traffic and travel in their areas to aid in planning services and targeting investment. The measure of travel usually adopted is that by people rather than by vehicle. This allows for a more meaningful measure of travel to be estimated, because, for example, a fully loaded bus carries far more people than a single car. These surveys can range over a designated area (e.g., a town or city), be concerned purely with journeys across a designated cordon, or may result from an individual or household travel diary.

Because the volume of total travel in different areas varies, it is common to present, for each mode, these volumes as a share of the total travel volume in the area and to express this share as a percentage. This then enables a comparison to be made of mode shares between areas. Also, if such surveys are conducted at regular time intervals, then trends in each mode of travel can be identified.

Concerns arise when these surveys are based on a small sample size, maybe as few as one full day of observation (Royal Statistical Society 2005; USDOT 2003). These small sample sizes should not, however, be much of a surprise since, typically, a six-hour survey in a large metropolitan area may cost upwards of £10,000 (about $18,000). Obtaining a more reliable estimate of the mode share and the precision of this estimate would require more survey days; just to halve the standard error of the mean estimate requires three extra days, bringing the cost of the survey to £40,000 (about $72,000). But without an indication of this sampling variability, it is difficult to conclude that any observed changes are real and statistically significant.

Some survey techniques, such as stated preference surveys, attempt to estimate mode share, and, since they use well-understood statistical models, they are able to provide confidence bounds around any mode share estimates (Ortuzar and Willumsen 1994). Such surveys are, however, typically concerned with making a choice that involves at least one hypothetical alternative. Furthermore, they have other errors that may lead to greater imprecision than already present and are costly to administer and analyze.

The study described in this paper focuses on an alternative form of data, namely revealed preference data, where the modes actually used by individuals are recorded. Also, this information is provided in an aggregate form of travel data (i.e., the number of people traveling by the different modes) rather than the disaggregate form of household or individual travel diaries.

MONTE CARLO SIMULATION

Simulation is an attempt to replicate a real world phenomenon using a model and a set of simplifying assumptions. One form of simulation that involves the assessment of the behavior of random variables (e.g., observed traffic flow or vehicle occupancy) is the Monte Carlo approach. The method assumes that the traffic flow (or other variable) follows a statistical probability distribution. As part of the simulation process, repeated instances of random observations are taken from this assumed distribution, and the impact of these random draws on some output measure is recorded. Using this simple sampling approach, many replications can be made, and a reliable estimate of the output measure and its spread can be obtained.

This paper uses the Monte Carlo approach to simulate the observed differences that can occur as a result of measurement error and daily variation associated with the conduct of a cordon traffic survey. By obtaining a large simulated set of these errors and variations and using them to "correct" the observed count, it will be possible to calculate a set of confidence intervals around the output measure, in this case mode share.

While results from the statistical literature allow the distribution for a mode share to be established (see appendix), this closed-form distribution approach contains a number of disadvantages:

- reliable estimates of the parameters for the distributions are difficult to obtain, because few sample observations are available;
- incorporating sophisticated multivariate relationships into the model is necessary, because, for example, the estimate of the share of travel by rail will impact on the share by all other modes; and
- the model and the methodology need to be easily explainable to nonstatisticians; mathematical models involving Greek symbols are not useful to such an audience.

Monte Carlo approaches have been used previously in the transportation field. These include structural reliability (Pothisiri and Hjelmstad 2003; Zhao and Ang 2003), traffic modeling (Cassidy et al. 1994; Tarko 2000), network reliability (Chen et al. 1999, 2002; Lam and Xu 1999), and activity modeling (Kreihich 1979; Veldhuisen et al. 2000; Castiglione et al. 2003).

Perhaps the most similar study to the work described here is that reported in Williamson et al. (2002), where the Monte Carlo approach was used to investigate whether short period traffic counts (of 5-, 10-, and 20-minute duration) can accurately represent hourly traffic counts. The first stage was to assume a Weibull distribution for the count data and to estimate the scale and shape parameters of the distribution. In the next stage, 1,000 instances of 60 observations (1 observation for each minute) from the appropriate Weibull distribution were generated and used to construct a cumulative distribution plot. From this plot, 90% confidence intervals were estimated, and if the actual observed hourly count fell within this interval then the estimation was deemed a success. An application of this methodology showed that contiguous 20-minute counts were required in order to accurately estimate an hourly traffic count.

SURVEY METHODOLOGY

This section describes the survey methodology used to collect the data for the example application of the Monte Carlo simulation. A thorough understanding of the survey methodology is important, because this will later help in defining the ranges for measurement errors and daily variations. All the data here (except rail data) were obtained from on-street observation by a team of enumerators, where all movements in one direction, across a datum line, were recorded. A discussion of the methodology for each mode of travel follows.

Cars. Each enumerator was asked to count the number of cars, categorized by the number of occupants (1, 2, 3, and 4 or more). Depending on the volume of traffic on the road, they may also have been required to count goods vehicles and cyclists.

Goods vehicles and cyclists. If the person who was counting cars could not handle this category of traffic, another enumerator was used to count these vehicles. Cyclists using dedicated paths or the pedestrian pavement were included in the count.

Buses. An enumerator recorded the type of bus observed and made a roadside assessment, without boarding the bus, of how full it was. Four types of buses were counted: mini, single deck, double deck, and articulated. The occupancy was recorded as empty, one-quarter full, half full, three-quarters full, full, and full with standing passengers.

Rail. The local Passenger Transport Executive (PTE) provided an estimate of the average volume of passengers arriving at the central train station. This estimate was based on onboard head count surveys conducted by train operator staff on three days during a year and was supplemented by additional PTE commissioned counts. They were then reconciled with other databases to provide an adjusted estimate.

Walk. The number of people walking across the datum line was recorded.

The surveys of the 34 radial roads into Leeds City Centre (figure 1) were conducted over 17 separate weekdays in May 2002 from 7:30 a.m. to 9:30 a.m. and 2:00 p.m. to 6:00 p.m. The number of radial roads surveyed on each day varied from one to up to five, but each road was counted only once.

The next two sections present ranges for the possible accuracy of the counts and the degree of daily variability during the morning peak. To a large degree, a Delphic approach (Dajani and Gilbert 1975), involving transport planners, survey managers, and statisticians, was used to arrive at a consensus opinion on the size of these error ranges. Other ranges may be used without invalidating the general Monte Carlo approach presented here.

MEASUREMENT ERROR

The measurement error assesses the accuracy of the enumerator counts. This is equivalent to comparing two (or more) counts of the same thing at the same time by different people to see how close they are in agreement. Clearly, this will depend on the skill and expertise of the staff involved.

Cars. The *Traffic Appraisal Manual* (DfT 2003) suggests that a skilled enumerator can achieve a 95% confidence interval accuracy of ±10%. Our own validation checks conducted by a second enumerator suggest that an interval of between ±5% and ±15% is usual. An error range of ±10% was selected for estimating the volume of single-occupant cars and a slightly larger range of ±12% for cars with more than one occupant, because this is a slightly more complex task.

Buses. It is likely that buses will be counted with more accuracy than cars, since they are a more visible presence on the road. Conversely, the measure of occupancy is likely to be inaccurate, because estimations of the occupancy must be made from the roadside. Table 1 gives the volume measurement and occupancy estimation errors for each type of bus. Minibuses have an error range similar to cars. All other bus types have a reduced error range, because they should be more noticeable. The error in estimating the occupancy of minibuses is low, because it is relatively easy for a quick and near precise estimate to be made. It is slightly more difficult to estimate the occupancy of single-deck buses. The most difficult task is estimating the vehicle occupancy of double-deck and articulated buses: with double-deck buses, it is very difficult to judge how full the top deck is; and with articulated buses, there is a large volume of information to assess visually. For these reasons, the occupancy error was set high at ±15%.

Rail. The PTE who provided the estimates for rail patronage judged the numbers to be accurate within a range of ±5%.

Walk and pedalcycle. Both these volumes are thought to be recorded at similar levels of accuracy to each other, near the ±10% mark.

Powered two-wheelers (PTWs). A PTW vehicle can be an inconspicuous part of the traffic. They do not necessarily keep to designated lanes and can easily speed along the carriageway or weave between lanes. This rational led to a high measurement error range of ±15%.

So far in this section, only the errors specific for each mode of travel have been quantified. In addition, it is not unreasonable to assume that there is a global error that affects all the modes counted on the same day. This may be due to generally unfavorable (foggy or wet) or favorable (dry and warm) roadside conditions. This global error is in addition to the mode-specific errors for all road-based volumes (i.e., not rail) and in this way modifies the mode-specific errors.

For the global volume errors, the range was set at ±5%. This means that, for example, a sample value for the error in estimating the volume of single-occupant car traffic was in the range of ±15% (a mode-specific element of ±10% and a global element of ±5%). Buses also have a global occupancy error to reflect the fact that in certain conditions (e.g., misty windows) occupancy in all buses will be difficult to estimate and also that rounding (to the nearest quarter) is involved. For buses, the global volume error was the same as for the other road-based modes, and the global occupancy error was set high at ±15%.

DAILY VARIATION

In addition to measurement error, taking into account the natural daily fluctuations that occur in traffic volumes is necessary. These variations can result from many causes; for example, a person may change his or her mode of travel or time of departure on successive days. Even if we were to count traffic with perfect accuracy, these daily variations will still be present in our data, and, in this section, estimates of the extent of these fluctuations are provided.

Cars. The daily variation in the volume of people traveling by car is specified for each category of car occupancy. These are set at ±5% for single- and double-occupant cars, ±8% for three-occupant cars, and ±12% for four or more occupants in a car. Some published evidence supports these ranges of variation. Phillips (1979) used a range of coefficients of variation of between 2.5% and 15% in determining the sample size for daily traffic flow estimation. Fox et al. (1998) suggested that a range for the coefficient of variation of 8% to 15% is appropriate, and, in the peak period, this value can be at the low end of this range (near 10%).

Buses. Buses run on a regular schedule each day, and, therefore, we would expect only small day-to-day variations in the number of buses counted. To quantify this, information reported in the 2003 West Yorkshire Local Transport Plan (WYPTA 2003) (which includes Leeds) shows that only 1.4% of all buses were canceled and of those that ran, 90% were less than 6 minutes late. In addition to this variation in the volume of scheduled buses, there was also variation in the average occupancy of buses. Both the volume and the occupancy variation are limited to ±5%.

Rail. Like buses, the volume of rail travel should be consistent from day to day. Statistics from the Strategic Rail Authority (2002) for the commuter rail operator in West Yorkshire show that the level of service reliability is comparable to that for buses. The percentage of train cancellations is 1.5%; however, the punctuality is slightly worse for trains, with just 83.8% of trains arriving within 5 minutes of their scheduled time (but 91.7% within 10 minutes). The range of variation was, therefore, set at ±5%, similar to the level for buses.

Walk. The volume of walk traffic is anticipated to vary slightly more than motorized methods of travel, because the traveler may easily substitute another mode (e.g., as a car passenger some days of the week or via bus on rainy days). The range was, therefore, set at ±10%.

PTWs. This mode is thought to be a highly variable form of travel. Statistics from the Department for Transport (1994) show that nearly 40% of motorcycle trips take place in the summer months and only 16% in the winter months. Many of these summer journeys will be for leisure purposes, and, because the primary concern here is with morning peak commuting trips, this suggests a range less than that indicated by the statistics. The range was set at ±12%.

Pedalcycle. Like walking and PTWs, this mode is thought to be highly variable on a day-to-day basis for many of the same reasons (DfT 1994, 1996). Cycling can, however, be even more unpleasant during adverse weather conditions than other modes (primarily for safety and comfort reasons) and so the variation range was set high at ±15%.

In addition to the mode-specific ranges of variation described here, an additional global element of variation was applied (in a similar manner to the global measurement error). This range of variation was set at ±5%. As a result, and referring to the values suggested for cars in this section, a compounded variation range of ±10% for single- and double-occupancy cars (a mode-specific element of ±5% and global element of ±5%) is possible.

MONTE CARLO SUMMARY

Before progressing to an illustrative example to show how this information is able to produce confidence intervals for mode share statistics, a few points are worth making.

- **Two distinct sources of uncertainty.** The measurement error represents the accuracy of the count, while the daily variability represents the fluctuation in these counts. Even if it were possible to count with 100% accuracy, there would still be daily variability, and, even if every traveler made the same journey by the same mode at the same time each day, there would still be differences in what enumerators counted.
- **Error structures.** Depending on the survey methodology adopted, the structure of the errors will change. If, instead of classifying cars by the occupants, one person counts both cars and people separately, it is likely that the measurement errors will be negatively correlated (i.e., they are able to count vehicles accurately but people inaccurately or vice versa).
- **Expertise required.** To set the ranges for the errors and variability requires some expertise and assumptions. One approach is to start with a fairly well understood measure (e.g., the accuracy in enumerating cars) and set other rates relative to this.
- **Count duration.** The range of daily variation will depend on the schedule of when counts are conducted. The ranges for a survey of 25 locations, all conducted on 1 day, should be larger than an alternative survey where 5 locations are counted on 5 days and their values summed.
- **Correlation between days.** In the model specified here, no correlation exists in the errors or the variation between consecutive days. If it appears that, for example, high errors in counting at locations on one day would lead to a tendency to high errors on other days, then this could be accommodated within the model framework presented here.
- **Limitations on model use.** The model is purely concerned with travel behavior in an aggregate form and no information on the traveler's individual characteristics (e.g., gender, age, income) is required or used. The model cannot, therefore, anticipate the detailed results of policy interventions or
- produce forecasts of future behavior.

EXAMPLE APPLICATION

To apply the Monte Carlo technique to the problem of estimating confidence intervals, we used the Excel spreadsheet package. Excel provides all the facilities required to conduct the simulation (primarily the generation of random numbers, although some care is required; see Knusel 1998). It has the tools to interpret the output (i.e., produce graphs and tables) and is commonly available.

One aspect that still needs to be defined is the underlying distribution from which the sample errors and levels of variation are drawn. The simplest distribution available is the *uniform* distribution where each sample value within a range is equally likely. This does not appeal intuitively, because smaller error or variability values would be more likely than larger values. This requirement suggests that the *normal* distribution should be used. The normal distribution does not, however, have a limiting range; sampled values can extend between plus and minus infinity. Clearly, these more extreme values would not be expected to arise in practice, so we adopted the convention that 95% of the sampled error or variability rates should be within the set ranges for errors or variability as described above. The normal distribution is also symmetric. If it is thought that the measurement errors are one sided (i.e., either mostly under- or overestimates), then it is possible to sample primarily positive or negative values.

The sampling regime as described in this paper is built within a workbook.[1] A series of 17 worksheets hold the morning peak data collected on each of the 17 survey days. Each of these worksheets contains the following traffic information for all sites that were counted on that survey day:

1. the existing base case as surveyed during May 2002,
2. the sampled values for the measurement error; these errors are applied to the observed counts so that the measurement errors they contain are "corrected,"
3. the sampled daily variations; these are applied to the "error corrected" values calculated in step 2 to represent values that could reasonably be counted on a different survey day,
4. the measurement error calculations for buses; these calculations are more complex, because they are disaggregated by the four vehicle types and six occupancy levels,
5. the final results are the updated counts after the application of both the measurement errors and daily variations.

A summary spreadsheet accumulates the updated counts for all 17 sites around the cordon to produce an overall estimate of the mode share.

The process of generating repeated measurement errors and daily variations was achieved with the aid of a simple Visual Basic macro and the resultant mode shares recorded and graphed. Figure 2 shows the distribution of the mode share for cars after 5,000 such samples were conducted, which took less than 5 minutes to calculate on a 2GHz desktop PC.

The distribution has a mean of 60.3% and a standard deviation of 0.71%. The distribution appears normal with an estimated skewness of 0.01 and an (adjusted) kurtosis of 0.06, both of which are close to the values expected for a normal distribution. It is, therefore, possible to estimate a 95% confidence interval for the car mode share between 58.9% and 61.7%. Similar confidence intervals can be calculated for the other modes. It should be noted that the resultant normal shape of this mode share distribution does not depend on the normality of the underlying sampling distribution; if a uniform sampling distribution is used, the same shape results, albeit, with a different spread.

SENSITIVITY ANALYSIS

The measurement errors used here could be improved on if further resources were devoted to data collection. As an illustration of this possibility, the question is posed as to what degree of improvement would result from a halving in the mode-specific error with which single-occupant cars are counted and classified, from 10% down to 5%. When the Monte Carlo simulation model is re-run with this new error range, the interval reduces only slightly to between 59.0% and 61.6%.

A wider view of how sensitive the measure of spread in the mode share of car is can be obtained by graphing the standard deviation for a series of values for one or more of the assumed ranges. Figure 3 shows how the standard deviation of the single-occupant car mode share changes as the single-occupant car-specific measurement error changes from 0% to 25% and the daily variation in single car occupants changes from 0% to 25%. All other ranges stay at their default values.

As expected, the standard deviation increases as the ranges of variation increase. Even at a 0% value for both ranges, variation remains in the mode share for cars. This is due to the fact that the other modes are still varying at their old levels, and, since we are dealing with a share, their variability will also impact on the variability of single-occupant travel by car.

SURVEY IMPLICATIONS

Information on the degree of variability of the car mode share statistic allows us to compute the minimum sample sizes required to reliably detect a specified level of change. Using the following equation for sample size estimation (Ortuzar and Willumsen 1994):

$$n' = z^2_{1-\frac{\alpha}{2}}\left(\frac{s^2}{\delta^2}\right)$$

where

n' is the required sample size,

$z^2_{1-\frac{\alpha}{2}}$ is the critical value of a α% standard normal distribution,

s is the estimated standard deviation of the measured quantity, and

δ is the minimum required change to detect,

and an example of an absolute one percentage point change as the target, the estimated sample size is:

$$n' = 1.96^2\left(\frac{0.71^2}{1.00^2}\right) = 1.94$$

which suggests that a sample size of two survey days is required to be 95% sure that an observed change of at least 1% in the average mode share for cars is significant. Table 2 shows the required sample sizes for a range of these changes for each of the three main modes of travel, using each of the Monte Carlo-derived estimates of the mode's standard deviation.

BOOTSTRAP ESTIMATION

The technique of bootstrap estimation falls within the resampling family of techniques (Efron 1982; Efron and Tibshirani 1993). It is particularly useful when no simple expression is available to compute the summary statistics for a measure or only a limited sample size is available. The process essentially involves taking repeated subsamples from a larger sample (with or without replacement) and calculating the statistic of importance based on this subsample. The distribution of these subsample statistics is then used to infer information about the population as a whole.

The bootstrap technique has had some application within the transport field. Rilett et al. (1999) used the technique to estimate the variance of freeway travel time forecasts derived from an artificial neural network. This allowed predictions to be made of future confidence intervals for journey times along a freeway and then used as input to Advanced Traveler Information Systems. A study by Brundell-Freij (2000) focuses on assessing the accuracy in the estimates produced by complex transport models. This study used both Monte Carlo simulation and bootstrap techniques to show how different kinds of variation in the input data affect the quality of the final model estimates. The study suggests that these variations can be a large but unknown feature of transport models. Hjorth (2002) used the bootstrap technique to estimate the covariance structure of traffic counts conducted at pairs of sites. This information was then used to construct route flow proportions and probabilities.

Here we are interested in using the bootstrap technique to obtain estimates of the mode share confidence intervals from a limited number of surveys (DiCiccio and Efron 1996; Wood 2004). If we have a count of the traffic entering the city center on a limited number of days at each site, it would be possible to choose, at random, one day from each site and add them together to arrive at an estimate of the total volume of traffic entering the city center and hence calculate mode shares. So, for example, one bootstrap draw could combine the counts from day five at site A, day two at site B, day one at site C, and so on, while the next draw would combine counts from day four at site A, day three at site B, day one (again) at site C, and so on. A large number of these draws could be taken and the distribution and summary statistics established for either the total volume or the mode shares.

Based on the Monte Carlo simulation work described earlier, additional surveys were conducted in May 2004, so that each radial road into Leeds City Center was surveyed on four days rather than the more usual one day. This sample size allows changes as small as 0.7% in the mode share for cars to be detected reliably. To increase the representative nature of the data, the survey was designed so that each of the 34 roads would be surveyed once on 4 different weekdays (excluding Fridays).

Aggregating the survey data together to produce a mode share for traffic crossing the entire cordon involved selecting 1 survey day from the 4 possible days at each of 34 survey locations. This produced a large number of possible combination of days and sites, 4^{34}, to be precise. To make this exercise more manageable, adjacent sites were grouped together to form seven corridors (see figure 1). This decreased the number of possible combinations to $4^7 = 16,384$. For the bootstrap exercise, just a fraction of these combinations were used: 4,000 selected at random from over 16,000 possibilities. The bootstrap mean of the 4,000 car mode shares selected was 57.3%, much lower than the Monte Carlo mean value calculated in 2002.

Table 3 gives the estimated standard deviations for the mode shares of car, bus, rail, and walk from the Monte Carlo and bootstrap techniques. The bootstrap-estimated standard deviation for car-based trips is 0.64%, compared with the Monte Carlo estimate of 0.71%. The bootstrap deviation could be expected to be different for a number of reasons:

- The range of daily variation selected for the Monte Carlo simulation was designed to account for the variety seen throughout the year, while the bootstrap estimate was based on just the variability observed within one calendar month. If the surveys used in the bootstrap estimation were conducted throughout 2004 rather than just in May, it is likely that a wider spread of observed variation would be present and the estimated standard deviation would increase above the 0.64% value found here.
- The survey enumerators knew there would be repeated surveys at each site. This ability to cross check counts may have encouraged them to be more accurate in their counting. A more accurate and consistent set of counts would produce a smaller deviation.
- The mean share was reduced significantly: the 0.71% Monte Carlo estimate is for a car share of about 60.3%, while the bootstrap estimate is a lower share of about 57.3%.

FURTHER IDEAS

In this paper, a Monte Carlo simulation regime was established to estimate the variability in mode share for a traffic cordon survey. While the illustrative example used a specific experimental methodology to collect the data and determine the structure of the model, the simulation approach proposed is flexible enough to allow the use of data that are collected through different survey designs. Of particular note here is that no "conservation of flow" principle has been applied to the changes (i.e., changes in one mode of travel are not mirrored with compensatory changes in another) but if thought necessary, this principle could easily be incorporated in the model.

There is nearly always a value in conducting more surveys to measure the important ranges that define both measurement errors and daily variation ("*Whenever you can, count*." Sir Francis Galton). These surveys do, however, come at a cost. The model proposed in this study can help to identify which survey methodology has the greatest impact on the accuracy of mode share and, therefore, provide the best value for the money.

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APPENDIX

Distributional Alternative

A question arises as to whether any results from the statistical literature will allow inferences to be made concerning the distribution of a share:

$$S_1 = \frac{X_1}{X_1 + X_2}$$

where

S_1 is the share of mode one,

X_1 is the volume of mode one,

X_2 is the volume of all other modes, and

the distribution of both X_1 and X_2 are known.

The γ distribution is one form of distribution that is quite flexible in the range of distributional shapes that it can represent. Another feature of the γ distribution is that if X_1 and X_2 are γ distributed random variables with $X_1 \sim \gamma(\alpha_1, \beta_2)$ and $X_2 \sim \gamma(\alpha_2, \beta_1)$, then S_1 has a β distribution, $S_1 \sim \beta(\alpha_1, \alpha_2)$. Critical to the use of this result is that both the γ distributions have similar values for the scale parameter, β_1.

In the context of the data used in this study, each mode of travel will have a different scale; the volume of travel by car is greater than that by bus and rail. This suggests that the β distribution approach to modeling the distribution of mode share may not be realistic.

END NOTE

1. Available from http://testcentral.bts.gov:8080/cgi-bin/ExitPage/good_bye.cgi?url=http://www.stephenclark.clara.net/.

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