Transferability Of Nationwide Personal Transportation Survey Data To Regional And Local Scales

Corresponding Author: Timothy R. Reuscher
Oak Ridge Institute for Science and Education
Phone: (865) 574-8690
E-Mail: reuschertr@ornl.gov

Richard L. Schmoyer, Jr.
Oak Ridge National Laboratory
Phone: (865) 574-1044
E-Mail: ric@ornl.gov

Patricia S. Hu
Oak Ridge National Laboratory
Phone: (865) 574-5284
E-Mail: psh@ornl.gov

All Authors:
Center for Transportation Analysis
Statistics and Data Analysis Program
Oak Ridge National Laboratory
P.O. Box 2008
MS-6073, Bldg. 3156
Oak Ridge, TN 37831-6073
FAX: (865) 574-3851

Submission Date: 07/30/2001 Revised: 10/27/2001
Note: Abstract + Text + References = 6529 words (with 1 table + 2 figures also attached, equivalent to 7329 words)

ABSTRACT

This paper details development of a system for using Nationwide Personal Transportation Survey (NPTS) data to estimate regional or local travel behavior—vehicle and person trips and miles of travel. This system can be used by state or municipal transportation planners.

The nation's Census tracts were classified into groups, or clusters, that tend to be homogeneous with respect to individual travel behavior. These Census tract clusters were based on household income, employment rate, number of household vehicles, and area type (urban, suburban, or rural). Then, NPTS data was used to estimate driving characteristics for each of the clusters derived in the classification step.

We then assessed how well the goal of estimating regional or local travel characteristics was achieved using "standards" computed from an independent survey from Baton Rouge, Louisiana, and independent data from three "add-on" components of the NPTS itself. Estimates computed from the NPTS data using the Census tract cluster method were compared with estimates computed from the standards, as well as to estimates computed from the NPTS data using competing methods where households were classified by size of the Metropolitan Statistical Area (MSA), Census Division, or Census Region. We found that in most cases the Census tract clustering method predicted travel better than the other methods, with small sample sizes generally being the cause when the Census tract method was not the best.

1. INTRODUCTION

In assessing the transferability of the Nationwide Personal Transportation Survey (NPTS) results to the regional or local level, one of our basic goals was to derive a system for using the NPTS data to estimate regional or local travel, including vehicle trips (VT), vehicle miles of travel (VMT), person trips (PT), and person miles of travel (PMT). Such a system could be used by state or municipal transportation planners. Assessing how good the estimates are would suggest appropriate scales to which the NPTS data might be broken down. If the scale is not too fine, the estimates will be good, and the estimation system could be used in practice.

Three steps were taken to achieve this goal. First, 59,828 of the nation's 61,258 Census tracts (CTs) were classified into groups that tend to be homogeneous with respect to travel behavior of people in the tracts. CTs which either had zero population or were Manhattan CTs were excluded. Manhattan tracts were excluded because previous studies indicated they were so different from other tracts that the national travel data should not be used as a basis for estimates about Manhattan. An additional 592 tracts were also excluded because they had no personal cars or trucks, and thus, for the purpose of estimating vehicle trips or VMT, were equivalent to tracts without population. Subsequent analysis also showed that these 592 tracts could reasonably be excluded for all travel, not just driving. Note that although the goal is CTs that are homogeneous with respect to travel behavior, the classification must be based on data available for all CTs, not just CTs containing households surveyed in the NPTS. That way the classification can be used to group all tracts, not just those for which NPTS data is available. The classification step is discussed in Section 2.

The second step was to use NPTS data to estimate driving characteristics for each of the CT clusters derived in the classification step. Data from the 19,880 CTs containing NPTS-surveyed households were used to estimate driving characteristics for each of the clusters derived in the first step. The estimation step is relatively straightforward—VMT and vehicle trips per household and person trips and PMT rates are computed for each cluster, household-size, and number-of-vehicles class. These rate estimates, as well as their standard errors, were computed using a SAS macro. This estimation step is discussed in Section 3.

With the classification and estimates derived in steps 1 and 2, travel estimates for any CT can be inferred from the tract's classification, and, given a region or community consisting of a mixture of CTs, travel characteristics for the community can be estimated from its distribution of clusters. The third step, then, was to assess how well the goal of estimating regional or local travel characteristics was achieved. To make this assessment, we used "standards" computed from independent data sources—data from an independent survey collected in Baton Rouge, Louisiana, and independent data from the New York, Massachusetts, and Oklahoma "add-on" components of the NPTS itself. Estimates computed from the NPTS data using the CT cluster method were compared with estimates computed from the standards, as well as to estimates computed from the NPTS data using alternative, competing methods. For the competing methods, estimates were also based on NPTS data, but, rather than having households classified according to properties of the CTs they are in, households were classified by the size category of the Metropolitan Statistical Area (MSA) they are in, the Census Division (CD) they are in, or the Census Region (CR) they are in. When estimates from reserved NPTS add-on data were used as standards, the reserved add-on data was not used to compute the estimates based on the CT cluster method or any of the competing methods. The assessment step is discussed in Section 4.

2. CLASSIFICATION OF CENSUS TRACTS

The main purpose of classifying CTs was to reduce estimation error to a reasonable minimum by determining a classification scheme that identified CTs with similar travel statistics. Estimation error is due to bias and variation, which includes sampling error and the natural variability of the thing being measured—VT, VMT, etc. For homogeneous classes, class-specific estimates tend to be less biased than general estimates. But although choosing homogenous classes tends to reduce bias, it also increases variability of estimates by decreasing sample sizes in the individual classes. Thus the key to obtaining a good classification is knowing how to split groups and when to stop splitting. Our classification of CTs was based on a combination of cluster analysis, regression analysis, judgement about data quality and outliers, and well known relationships between VT or VMT and various predictor variables including area type (rural, urban, suburban), income, employment, and numbers of vehicles. Although VT and VMT were the primary focus in this decision-making, PT and PMT were also considered, and the validation tests in Sections 3 and 4 show that the classification scheme derived also works well for PT and PMT.

2.1 Preliminary Analysis

The first step in our process involved establishing a relationship between explanatory variables and travel (as represented by VMT) through a regression analysis of the NPTS data. Explanatory variables included income, household size, employment rate, two age variables, and latitude and longitude. Income, household size, and employment rate emerged as the three most important variables in predicting VMT and VT. Other variables were also significant, but they added no significant explanatory power beyond that provided by the three most important variables.

Next, we used these three variables as part of a preliminary cluster analysis on the CT data to separate the 59,828 CTs into homogeneous groups. Since three variables were used, $2^3 = 8$ clusters were specified for the initial analysis. This analysis, however, produced several overlapping clusters, which suggested that some clusters should be combined. On the other hand, combining clusters seemed to lead to too few clusters to sufficiently resolve trip and mileage rates.

Further examination of the preliminary eight clusters indicated that they tended to differ in area type, with each cluster being predominantly, either urban, suburban, or rural. The suburban, urban, and rural area type designation is based on an NPTS classification of CTs into five area types: urban (U), suburban (S), rural (R), town (T), and second city (C) (*1*). However, the Bureau of Transportation Statistics (*2*) indicates that in terms of VT, as measured by the 1995 NPTS, the area types rank as follows: C > S > T > R > U. For VMT, the ranking is R > T > S > C > U. This suggests that second city and suburban (C and S) tracts might be combined into a single "suburban" group, and that rural and town (R and T) tracks might be combined into a single “rural” group, but that urban tracks should be kept separate. Therefore we decided to use this urban-suburban-rural classification scheme to refine the eight-cluster analysis.

In addition, we suspected that outliers in the income variable were affecting the results of the preliminary cluster analysis. For example, five tracts had median household incomes of $0 and three tracts had median household incomes of $375,000 or more. Therefore, as described next, our final cluster development segregates very high and very low income CTs, and then classifies the remaining tracts according to their urban-suburban-rural area type as well as the original three variables, household size, employment, and income.

2.2 Final Cluster Development

The ultimate goal in the classification was to minimize errors made in local or regional travel estimates computed from NPTS data. However, because it is well known that classification algorithms such as cluster analysis sometimes lead to difficult-to-interpret classification schemes, another goal was a classification that makes sense in light of the known relationships. Thus, the classification system we finally arrived at was based on both analysis and judgement. As seen in Figure 1, the system splits off very high and very low income groups, then splits the remaining CTs by urban-suburban-rural area type, and finally clusters them by the income, household size, and employment rate.

The classification system first splits off 1,634 very low (median income less than $12,000) and 1,804 very high income (median income greater than $75,000) tracts into their own respective clusters. The very low and very high income tracts were split off into their own clusters for several reasons. One reason was to prevent tracts that are outliers with respect to income from unduly influencing classification of the remaining tracts. However, splitting off high and low income tracts is also reasonable because of what we know about the relationship of income and driving: For people in the highest income classes, driving habits are not likely to be further affected by income. Furthermore, the highest income cluster is predominantly suburban, so further classification by area type would not be useful for the very high income cluster. The very low income cluster, on the other hand, generates relatively little VMT and VT. The very low income tracts also consist primarily of urban and second city tracts, suggesting that for very low income CTs, the NPTS second city (C) group may be closer in driving patterns to the urban (U) than to the NPTS suburban (S), and that grouping the NPTS C and S tracts into a single suburban group, though reasonable overall, might be inappropriate for very low income tracts.

After splitting off the very high and very low income tracts, the remaining 55,798 intermediate income tracts were next classified by area type (suburban, urban, rural). The combined suburban class for these intermediate income tracts is composed of 49% S and 51% C and the combined rural class is 42% T (town) and 58% R (NPTS rural). The resulting three combined area-type classes had the following numbers of tracts: Urban: 10,238; Suburban: 21,564; Rural: 23,996.

It is unrealistic to expect a statistical procedure such as cluster analysis to "cleanly" classify CTs on the basis of socioeconomic variables such as income, employment, and household size. Therefore, to get a classification of the intermediate income tracts that was more clearly interpretable, we ran the clustering with a separate cluster analysis for each area-type group, but with only three clusters per area type. Using household income, average number of vehicles per household, and the employment rate for the tract, for each area-type, we determined three clusters representing "low," "middle," and "high" economic strata. The definitions of low, middle, and high are relative within each area-type. The 10,238 urban tracts were split into 3,059 low, 4,565 middle, and 2,614 high tracts. The 21,564 suburban tracts were split into 5,136 low, 9,865 middle and 6,563 high tracts. And the 23,996 rural tracts were split into 6,604 low, 11,722 middle, and 5,670 high tracts. The intermediate income tracts were thus classified into nine groups. The decision to stop splitting was based on standard errors and validation results discussed in Sections 3 and 4.

3. ESTIMATION OF TRIP AND MILEAGE RATES

The U.S. Census Bureau estimates numbers of households by household-size or number-of-vehicles classes, for each CT. Given VT and VMT estimates from NPTS for the various household-size or number-of-vehicles classes, transportation planners can use the Census Bureau frequencies to estimate total VT and VMT originating in any tract, or in any collection of tracts. The estimates are simple sums over household-size or number-of-vehicles classes of the products of the per-household VT or VMT rates and the frequencies of households in the class. How good these total VT or VMT estimates are obviously depends on how good the per-household rate estimates are. Although the size of a household and its number of vehicles are good determinants on average of the VT and VMT a household generates, per-household rates also vary with other factors such as income and area-type.

According to the Census Bureau, CTs are "designed to be relatively homogeneous units with respect to population characteristics, economic status, and living conditions at the time the CSAC [census statistical areas committee] established them" (*3*). Therefore, although household size and number-of-vehicles-specific VT and VMT rates vary from census tract to census tract, it is reasonable to expect these rates to be relatively homogeneous within any given tract. The goal of the classification in Section 2 is to group CTs into clusters for which explanatory variables of VT and VMT, and thus the VT and VMT rates themselves, are relatively homogeneous. Then VT and VMT originating in a given CT can be estimated well from the joint household size and number-of-vehicles distribution and from VT and VMT rates specific to the cluster (e.g., urban "middle").

Household-size, number-of-vehicles, and cluster-specific VT and VMT rates were calculated from 1995 NPTS data using a SAS standard error macro (*4*). In addition to rate estimates, the macro is also used to calculate standard errors of the estimates, weighted with the NPTS sampling weights, using the ultimate cluster variance formula of Hansen, Hurwitz, and Madow (*5*). Estimates and standard errors for each final cluster, household-size class, and number-of-vehicles class were developed. For these estimates, there are five household sizes classes (1–4 and 5 or more) and four vehicle size classes (0, 1, 2, and 3 or more). Similar estimates for PT and PMT were also developed.

Standard errors together with validation results discussed below were used to decide when to stop splitting in the classification of CTs. The standard errors were not used directly, however. VT and VMT rates for household-size and number-of-vehicle classes are mainly used in practice as multipliers for estimating VT and VMT totals for areas with known household-size and number-of-vehicle-specific frequencies. Thus the totals—rates for whole areas—are the main objective, not the rates for individual household-size and number-of-vehicle classes. Therefore, for decisions about when to stop splitting, we looked at the relative standard errors of the weighted-average rate estimates computed for each cluster by averaging over household-size and number-of-vehicle classes, with weights computed by summing the individual household weights. The weighting thus reflects cluster-specific national averages for the distribution of households in household-size and number-of-vehicle classes. Although the distributions do vary from community to community, weights based on national averages are reasonable for an overall criterion.

In general we sought a clustering for which the relative standard errors of the rate estimates, combined over household-size and number-of-vehicles classes, were on the order of 2 to 5% for each cluster. A relative error of 5% translates to a 95% confidence interval of about plus-or-minus 10% (two standard errors). "On the order of" is also operative here: a clear sensible classification was also a target in the decision to split or not to split groups. In practice, of course, rate estimates for individual clusters are usually combined, because communities are usually composed of tracts from several clusters. In those cases, cancellation of errors works to make overall errors smaller on average. This is illustrated in the validation estimates for the NPTS add-ons and Baton Rouge, discussed in the next section.

We computed class-specific relative standard errors for VT and VMT estimates. These relative errors seem mostly related to sample size (number of households in the cluster), which suggests that variance and not bias is the main source of error and that further splitting would not reduce overall error (bias and variance). The 2-5% goal was achieved except in the very low income and "low" urban clusters. Those clusters are small, however, and generate relatively few trips. Thus VT and VMT rate estimates for those clusters are less critical than for many of the other classes. This is also illustrated in the results for Baton Rouge and the NPTS add-ons, found in Section 4.

4. ASSESSMENT OF THE ESTIMATION METHODS

In this section we assess the performance of the CT cluster estimators by comparing them to three alternative estimators. The alternative estimators are similar to the CT cluster estimators, but are based on groupings defined in terms of either MSA size, CR (census region) or CD (census division), rather than the CT clusters defined above. The CT cluster and alternative estimates are computed from NPTS data for New York, Massachusetts, Oklahoma, and Baton Rouge, Louisiana. The CT cluster and alternative estimates are compared to "standards" to assess the performance of the estimation methods. For Baton Rouge estimates, the standards are estimates computed from an independent Baton Rouge transportation survey obtained from Steve Greaves of the Lafayette, LA Traffic and Transportation Department (unpublished data). For the New York, Massachusetts, and Oklahoma estimates, the standards are based on data reserved from the New York, Massachusetts, and Oklahoma over-sample components of the NPTS.

Reserved data is not used to compute the CT cluster or alternative estimates. Therefore, in all cases, the reserved-set "standard" data is statistically independent of the data used to compute the estimates, and none of the methods could appear good since estimates are computed from different data than the standard. Although the estimates and reserved-set standards are statistically independent, they are all based on sample survey data. Therefore standard errors for both estimates and reserved-set totals are computed and related to the estimates and reserved-set totals in interpreting their differences.

Data sources and the general approach to the assessments are discussed in Section 4.1. In Section 4.2 we discuss bias in the NPTS data, due to under-coverage or non-response, which could affect comparisons of NPTS-based estimates with estimates computed from other data sources. In Section 4.3 and 4.4 we consider comparisons of the estimation procedures. Preliminary CT-cluster-specific comparisons, and comparisons by trip purpose and mode are discussed in Section 4.3. As these comparisons require much detail to elaborate, they are only described briefly. Section 4.4 is about overall comparisons of VT, VMT, PT, and PMT estimates, not broken down by categories such as CT clusters or trip purpose or mode. Because these comparisons provide an overall assessment of the performance of the CT cluster estimates, they are considered in detail, specifically for each data source.

4.1. Assessment Methods

4.1.1. Data Sources

Our assessment was based on four data sets—one from Baton Rouge, and three from 1995 NPTS add-ons. The Baton Rouge data comes from a survey performed between April 17,1997 and July 9, 1997. The survey was of 1,395 households from greater-area Baton Rouge, and asked the same questions, in the same format, as in the NPTS. However, several differences do exist between the basic designs of the two surveys. For example, the NPTS had substrata, but the Baton Rouge survey did not. In addition, the Baton Rouge survey was conducted only in late-Spring/early-Summer, whereas the NPTS was conducted for longer than a year. Thus, the Baton Rouge data may be seasonally biased. Also, the Baton rouge survey was performed a full year after the NPTS. Since trip rates generally increased over time, and are also affected by cyclical phenomena such as gasoline prices and the general economy, the time gap between the NPTS and Baton Rouge surveys could contribute to differences in trip rates. These differences may bias comparisons of estimates computed from NTPS and Baton Rouge data.

The New York, Massachusetts, and Oklahoma data sets used to assess the NPTS-based estimates actually consist of observations reserved from the complete NPTS data. By recomputing the estimates discussed in Section 3 using the NPTS data without the reserved set, estimates for each of these three areas can be computed and compared to results for the corresponding reserved data (which thus serves as an independent standard), as well as three other competing methods. This approach is reasonable because of the oversampling for these three areas in the NPTS: 11,004 of the 42,033 NPTS surveyed households are in New York, 7,801 are in Massachusetts, and 3,932 are from oversampled areas of Oklahoma. These comparisons should be more reliable than comparisons involving Baton Rouge since survey differences will not be compounded with differences among methods.

Data from the New York add-on was randomly split into two equivalent subsamples, with one of the subsamples serving as reserved data. For assessing estimates for New York, however, the reserved data was not used to compute the estimates. To account for this, sampling weights for New York observations in both the remaining NPTS data and the reserved data were multiplied by two. When half of the New York sample is reserved, the sampling probabilities for the remaining New York observations are half of what they otherwise would have been. Therefore the sampling weights for the remaining New York observations should be adjusted to twice their original values. The same argument applies to the reserved New York data. Although post-sample-selection weight adjustments are not applied to either the reserved or main sample (after excluding the reserved subset), the weights still sum to fairly close approximations of the known totals, and various other weight sums for New York, Massachusetts, and Oklahoma also show general agreement between subsamples.

This same half-sample subsampling and reweighting procedure was also applied to the Massachusetts add-on. The Oklahoma add-on actually consisted of two add-ons: Central Oklahoma and Tulsa. Combined, these add-ons account for 3,932 sampled households. Since the add-ons did not cover certain parts of the state, there were an additional 141 Oklahoma households sampled for inclusion in the NPTS sample, but these Oklahoma households were not considered as part of the Oklahoma add-on. Treatment of the Oklahoma add-on was the same as for New York.

4.1.2. Assessment Estimates

Five sets of estimates were computed for each of the PT, PMT, VT, and VMT totals: the estimates computed using the CT clustering approach, the MSA-size, CD, and CR approaches, and the "standard" estimates, which were computed from the reserved NPTS data or the Baton Rouge survey. For the CT cluster approach, we take the weighted number of households in each cluster, household-size, and vehicle-count group that are found in the reserved-set data, and multiply them by the national NPTS rate for that group. We then sum over cluster, household-sizes, and vehicle-count groups to get totals to compare with the reserved-set totals. Estimates based on MSA size classes are similar: the weighted number of households in each household size-vehicle count group is multiplied by the national NPTS rate for households in that MSA size class. For Baton Rouge, however, there is only one MSA size class (population between 500,000 and 999,999), while there are multiple MSA size classes for the NPTS add-ons. For the CD and CR approaches, we take the weighted number of households in each household size-vehicle count group, and multiply them by the NPTS rate for the division or region for the appropriate group.

Our Census data, the 1990 STF3A data set arranged by CT (*6*), have counts of households by either size or number of vehicles, but, unfortunately, not by both household size and number of vehicles jointly. We have nevertheless assumed that the joint size-by-number-of-vehicles breakdown will be available to transportation planners. In lieu of the joint breakdown, we used an estimate of it computed from the NPTS sampling weights. This should not have much effect on comparisons of the NPTS with the validation of the three add-ons or BR estimates, however, because, in the error assessment, the weights only serve to define an integration over classes to a combined error assessment. The combined error assessment is not sensitive to minor changes in the weights.

If a transportation planner also happens not to have the joint size-by-number-of-vehicles breakdown, but had the breakdown by either household size or vehicle size class, the CT cluster method can still be used, and without much change. The estimates in Section 3 could be computed by cluster and household size only, for example, and used to compute estimates based on that two-way classification. The same methods could, in fact, also be used with finer classifications. For example life-cycle (singe adult, no children; two or more adults, no children; etc.) could be included with cluster, household size and number-of-vehicles in a four-way classification. Although geographic location appears less important than income, employment, or number of vehicles per household, location might also be a good candidate for refining the estimators.

4.2. NPTS Bias

The NPTS is a scientifically designed survey based on probability sampling. Sampling weights, which are used to weight estimates computed from NPTS data, are calculated to reflect the selection probabilities and also to adjust for non-response and non-coverage. Nevertheless, the NPTS is a telephone survey—sampling is from lists of telephone numbers—and so both non-coverage and non-response could induce bias in estimates based on the NPTS. The issue of bias is fundamentally important here, because we are comparing estimates based on NPTS data to independent estimates from Baton Rouge.

Measuring bias in NPTS data requires a reference data source that is independent from the NPTS and yet comparable to it in terms of both coverage and numbers of observations. Although the Census data used here does not provide such a reference for VT or VMT, it does provide comparisons in terms of income, vehicle ownership, and employment. Because of the correlation between these variables and travel, biases in these variables could indicate the extent of bias in NPTS VT and VMT data. For each of these variables, the NPTS appears to be slightly biased on the high side, which suggests that the same may be true for VT, VMT, PT, and PMT. This conclusion should be kept in mind when considering comparisons of the NPTS with other data sources.

4.3. Preliminary and Finer-Level Comparisons

In addition to overall comparisons (Section 4.4) of the standard to CT cluster, MSA-size, and CR and CD estimates, several comparisons were made at finer levels. The CT cluster estimates are computed by estimating cluster-specific trip and mileage rates per household, and by summing up the products of the rates and household totals for the clusters. As illustrated in Figure 2, the cluster-specific errors tend to cancel in the accumulated estimates. Although these cluster-specific estimates are incidental to the final CT cluster-based estimates, errors in cluster specific estimates suggest that the clusters should be divided (or redefined), and these errors were considered in deciding whether the number of clusters was sufficient.

Estimates can also be computed for specific trip purposes (e.g., to work or school) or modes (e.g., public transportation). Although mode and purpose-specific estimates, as well as overall estimates, are an ultimate objective in deriving the CT cluster estimators, the mode and purpose-specific estimates are more complex, and, because they are based on data disaggregated into subsets, statistically less reliable. Therefore mode and purpose-specific estimates are not considered further in this paper (but will be considered in a forthcoming report).

4.4. Assessment Results—Overall Comparisons

For all four of our examples (New York, Massachusetts, and Oklahoma, and Baton Rouge), we compared the VT, VMT , PT, and PMT standard totals to NPTS totals for the CT cluster, MSA size, CD, and CR methods. Thus, we compared the CT cluster estimates to the standard data, as well as to other estimates computed from the NPTS data, using competing methods. These estimates are shown in Table 1.

4.4.1. New York Add-On

For the New York add-on, the CT cluster approach was more accurate in estimating all four trip and mileage measures than the MSA size, CD and CR approaches. The MSA-size approach did reasonably well, while the two approaches based on Census areas were anywhere from 19 to 36% off of the New York reserved-set totals. Thus, the remainder of the comparison of New York results takes into account only the cluster and MSA-size approaches.

Person trips were estimated by the CT cluster method to within 2.36% of the 53.7 million New York reserved-set total, or slightly more than one standard error (2.16%). Using MSA size rates in conjunction with New York households resulted in an error of almost exactly two standard errors (4.31%). The CT cluster approach estimates vehicle trips to within 0.63% of the 28.7 million daily observed trips, while using MSA-size estimates trips to within 2.36%. The CT cluster approach was clearly better than the MSA-size method in estimating the numbers of trips.

The CT cluster approach also did better than the MSA-size method in PMT and VMT estimates, though not as overwhelmingly. The cluster method predicts PMT to within 4.37% of the daily 459 million reserved-set total miles, while using MSA-size-based rates estimates PMT with a 5.56% error. The standard error of reserved-set PMT is 4.37%, meaning that the cluster method is exactly one standard error off, and the MSA-size method is a bit over one standard error away. With a VMT standard error of 3.7%, both approaches predict the 256 million daily vehicle miles taken by New Yorkers within one standard error, with the CT cluster approach being off by 2.62%, and the MSA-size approach off by 2.87% of the reserved-set total. In each comparison estimating the New York reserved-set totals, the CT cluster approach does better than the MSA-size approach, with the largest disparities between the two methods coming in person and vehicle trips.

4.4.2. Massachusetts Add-on

As in the New York example, the CD and CR estimates poorly estimate Massachusetts trip and mileage totals (Table 1). Hence, the comparison of methods to estimate Massachusetts reserved-set totals will focus on the differences between the CT cluster approach and the MSA-size approach.

The CT cluster method estimated Massachusetts person trips to within 1.11% of the 22.9 million daily trips taken. Estimates from the MSA-size approach were also close to actual totals, being 2.06% (and less than one standard error of 2.2 %) lower. For PMT, the CT cluster estimates were a mere 0.13% higher than the 202 million daily person miles taken by Massachusetts residents. The totals obtained using the MSA-size method were off by quite a bit more (3.92%), although they were still within one standard error (4.14%).

Vehicle trips and VMT estimates for both methods were not quite as accurate as those for person trips and PMT. Estimates of vehicle trip totals from the CT cluster approach were 5.26% lower than the actual 14.7 million daily trips seen in the totals. This number is more than two times the standard error for Massachusetts vehicle trips (2.2%). The MSA-size approach did even worse, being more than 10% lower than reserved-set total. A similar trend emerged in the VMT portion of the analysis. The CT cluster method was 6.4% lower than the Massachusetts total of 131 million daily vehicle miles. This placed the cluster estimate nearly two standard errors away from the reserved-set total. The MSA-size method continued to do relatively poorly in predicting Massachusetts vehicle travel, being more than 10% (or more than three standard errors) away from the reserved-set VMT totals. The Massachusetts add-on data provides the clearest example of the superiority of using the CT cluster approach as opposed to simply computing statistics based simply on an area's MSA size**.**

4.4.3. Oklahoma Add-on

The CD and CR approaches did much better in estimating the reserved-set totals for Oklahoma than New York or Massachusetts. In fact, the best approach in estimating person trips was the CD method, estimating person trips at only 0.1% less than the 6.5 million daily trips taken by Oklahoma households. The CT cluster approach was second-best, falling 0.2% short of the reserved Oklahoma total. The MSA-size and CR methods were third and fourth-best. However, all of the methods were within one standard error of the reserved Oklahoma total. Vehicle trip estimation followed a similar pattern, with the CD approach a little under one percent of the 4.3 million daily vehicle trips taken. The other three methods, with the CT cluster approach being second best, were within one and two standard errors of the reserved Oklahoma total.

Mileage estimation analysis showed a different picture. The best approach in estimating PMT was the cluster method, coming within 1.92% of the 59 million daily person miles traveled by Oklahoma households. The MSA-size method was second best, coming within 2.21% of Oklahoma totals, and still well within one standard error (4.24%). CR and CD estimates of PMT were substantially worse, with the CR method off by 7.96%, and the CD approach off by a relatively huge 17.1%. A similar situation occurred in the VMT analysis. The CT cluster method was again best coming within 0.26% of the 37.6 million daily vehicle miles. The MSA-size approach was again second best, coming within 1.61%, or about half of one standard error in the reserved-set totals. The CD and CR estimates were within one to three standard errors, with the CD numbers again being the worst. Despite the closeness of the trip estimates, this huge disparity in mileage estimates suggests that the CT cluster approach is better than the CD method in estimating Oklahoma travel statistics overall.

4.4.4. Baton Rouge

No single estimation method did uniformly well when compared to the Baton Rouge PT, PMT, VT, and VMT standard totals. The CT cluster approach estimated person trips extremely accurately, coming within 0.12% of the Baton Rouge total of 1.6 million daily trips. The MSA-size approach, however, yielded similar results, off by only 0.14%. Both approaches are excellent given a standard error of 2.86% of the Baton Rouge totals. CD and CR estimates were also good, off by 3.34% and 2.23%, respectively. PMT was estimated best by the MSA-size approach, coming within 1.69% of the Baton Rouge totals of 15.1 million daily person miles. The CT cluster approach, as well as the CR approach, were also good, estimating PMT within one standard error. The CD approach was by far the worst in estimating PMT, being almost 14% off of the Baton Rouge totals.

However, the CD approach excelled in predicting vehicle trips and VMT for Baton Rouge. This approach estimated vehicle trips within 3.45% of Baton Rouge totals of 1.1 million vehicle trips, a shade over one standard error. The other three approaches estimated vehicle trips within approximately three standard errors. The CD approach was also extremely accurate for VMT, estimating Baton Rouge numbers of 10 million vehicle miles to within 1.18%. The CR approach was good as well, coming within 3.28%. The MSA-size and CT cluster approaches estimated VMT to around 10 to 12%, respectively, or just a bit over two standard errors. The CT cluster approach was not the best overall approach in estimating the Baton Rouge data. In view of its superior performance for the NPTS add-ons, however, we believe this is probably due to differences between the Baton Rouge and NPTS data, induced by procedural differences and time-scope biases.

5. CONCLUSION

The results presented here are based on only four examples from New York, Massachusetts, Oklahoma, and Baton Rouge. Many more comparisons are needed to definitively establish which method is best, and to develop a general indication of whether any of the approaches lead to estimates that are adequate. In this regard, the upcoming releases of the 2000 Census and 2001 National Household Travel Survey (NHTS) will provide much additional data. The 2001 NHTS data will have nine add-on components. Additional data may also suggest refinements to the current CT clustering scheme (Figure 1).

Nevertheless, on the basis of the four examples considered here, the overall performance of the CT cluster method (Tables 1) suggests that it is the best approach in general. It was better than all other approaches in estimating trip and mileage totals for the New York and Massachusetts data and was the best overall in estimating Oklahoma data. The CT cluster approach was not best is in estimating VT and VMT for the Baton Rouge data, or VT in Oklahoma. However, we believe that is probably due to procedural and time-scope differences between the Baton Rouge and NPTS surveys, or to statistical error. Of the four examples, Baton Rouge and Oklahoma had by far the smallest sample sizes, and so the standards for these data were subject to the greatest sampling error.

The second best method appears to be the MSA-size approach, but in two instances (VT and VMT for the Massachusetts add-on), the MSA-size approach failed to come within three standard errors of the reserved-set standard, while the CT cluster error was three standard errors or less. As a data set associating each CT with the CT clusters (derived as above) will be available from the authors, the CT cluster approach will not be appreciably harder to implement than the other methods. Therefore, on the basis of these limited results, the CT cluster method appears to be the best approach.

As the CT cluster approach is based on the entire NPTS data, statistical error of the CT estimates is typically much smaller than the statistical error feasible in local surveys. Keeping in mind that rates from the 1995 NPTS do not reflect potential increases over time occurring since that NPTS was conducted, transportation planners can use the CT cluster approach to estimate regional and local VT, VMT, PT, and PMT. As with all statistical estimates, computation and examination of standard errors is also essential for ensuring that the estimates are adequate for the task at hand.

ACKNOWLEDGEMENTS

The authors would like to thank the Federal Highway Administration's Office of Highway Policy Information for funding this research and, in particular, Susan Liss for the concept of transferring the results of the NPTS to smaller communities.

REFERENCES

1. Federal Highway Administration. *User's Guide for the Public Use Data Files: 1995 Nationwide Personal Transportation Survey*. Report FHWA-PL-98-002. FHWA, U.S. Department of Transportation, 1997.

2. Bureau of Transportation Statistics. *Transportation Statistics Annual Report 1999.* Report BTS99-03. BTS, U.S. Department of Transportation, 1999

3. U.S. Census Bureau. Glossary of Basic Geographic and Related Terms. http://www.census.gov/geo/www/tiger/glossary.html. Accessed January 22, 2001.

4. Schmoyer, Rick. Standard Error Calculations for NPTS Estimates. http://www-cta.ornl.gov/npts/1995/Doc/se.pdf. Accessed January 22, 2001.

5. Hansen M. H., Hurwitz, W. N., and Madow, W. G. *Sample Survey Methods and Theory.* John Wiley & Sons, New York, 1953.

6. Center for International Earth Science Information Network. Archive of Census Related Products. http://sedac.ciesin.org/plue/cenguide.html. Accessed December 6, 2000.

LIST OF TABLES AND FIGURES

TABLE 1 Comparison of Methods to Baseline Standards

	New York	SE as %	CT Cluster Rates	Pct diff	MSA Size Rates	Pct diff	CD Rates	Pct diff	CR Rates	Pct diff
PT	53,657,551	2.16%	52,389,300	**-2.36%**	51,344,771	-4.31%	38,462,883	-28.32%	41,745,500	-22.20%
PMT	459,178,922	4.37%	439,123,402	**-4.37%**	433,631,520	-5.56%	291,870,089	-36.44%	330,857,392	-27.95%
VT	28,653,474	2.04%	28,835,004	**0.63%**	27,977,015	-2.36%	20,960,605	-26.85%	23,202,606	-19.02%
VMT	255,795,187	3.71%	249,083,376	**-2.62%**	248,447,090	-2.87%	175,011,971	-31.58%	198,455,142	-22.42%

	Massachusetts	SE as %	CT Cluster Rates	Pct diff	MSA Size Rates	Pct diff	CD Rates	Pct diff	CR Rates	Pct diff
PT	22,905,841	2.20%	22,650,765	**-1.11%**	22,434,511	-2.06%	16,892,483	-26.25%	20,102,290	-12.24%
PMT	202,132,709	4.14%	202,387,508	**0.13%**	194,204,818	-3.92%	153,415,946	-24.10%	167,192,631	-17.29%
VT	14,684,173	2.20%	13,912,160	**-5.26%**	13,176,923	-10.26%	10,475,399	-28.66%	11,974,009	-18.46%
VMT	130,907,651	3.23%	122,510,744	**-6.41%**	117,071,084	-10.57%	94,120,125	-28.10%	102,768,840	-21.50%

	Oklahoma	SE as %	CT Cluster Rates	Pct diff	MSA Size Rates	Pct diff	CD Rates	Pct diff	CR Rates	Pct diff
PT	6,463,309	2.88%	6,449,930	-0.21%	6,505,491	0.65%	6,456,894	**-0.10%**	6,335,251	-1.98%
PMT	59,150,730	4.24%	60,285,795	**1.92%**	60,457,496	2.21%	69,268,367	17.10%	63,860,543	7.96%
VT	4,337,423	2.51%	4,211,490	-2.90%	4,148,946	-4.35%	4,296,229	**-0.95%**	4,200,352	-3.16%
VMT	37,623,890	4.05%	37,720,723	**0.26%**	37,017,886	-1.61%	41,608,888	10.59%	40,065,992	6.49%

	Baton Rouge	SE as %	CT Cluster Rates	Pct diff	MSA Size Rates	Pct diff	CD Rates	Pct diff	CR Rates	Pct diff
PT	1,587,151	2.86%	1,589,117	**0.12%**	1,589,342	0.14%	1,640,108	3.34%	1,551,680	-2.23%
PMT	15,123,606	5.09%	14,481,770	-4.24%	14,868,548	**-1.69%**	17,233,175	13.95%	15,570,362	2.95%
VT	1,094,716	2.84%	1,000,793	-8.58%	1,010,047	-7.73%	1,057,001	**-3.45%**	1,016,777	-7.12%
VMT	9,983,730	4.86%	8,789,907	-11.96%	8,972,263	-10.13%	10,101,720	**1.18%**	9,655,903	-3.28%

	Overall (simple totals)	SE as %	CT Cluster Rates	Pct diff	MSA Size Rates	Pct diff	CD Rates	Pct diff	CR Rates	Pct diff
PT	84,613,852	1.51%	83,079,112	**-1.81%**	81,874,115	-3.24%	63,452,368	-25.01%	69,734,721	-17.58%
PMT	735,585,967	2.98%	716,278,475	**-2.62%**	703,162,382	-4.41%	531,787,577	-27.71%	577,480,928	-21.49%
VT	48,769,786	1.39%	47,959,447	**-1.66%**	46,312,931	-5.04%	36,789,234	-24.57%	40,393,744	-17.17%
VMT	434,310,458	2.42%	418,104,750	**-3.73%**	411,508,323	-5.25%	320,842,704	-26.13%	350,945,877	-19.19%

Percent differences in bold indicate the closest method of baseline estimation for a given statistic

FIGURE 1. A Classification of Census Tracts

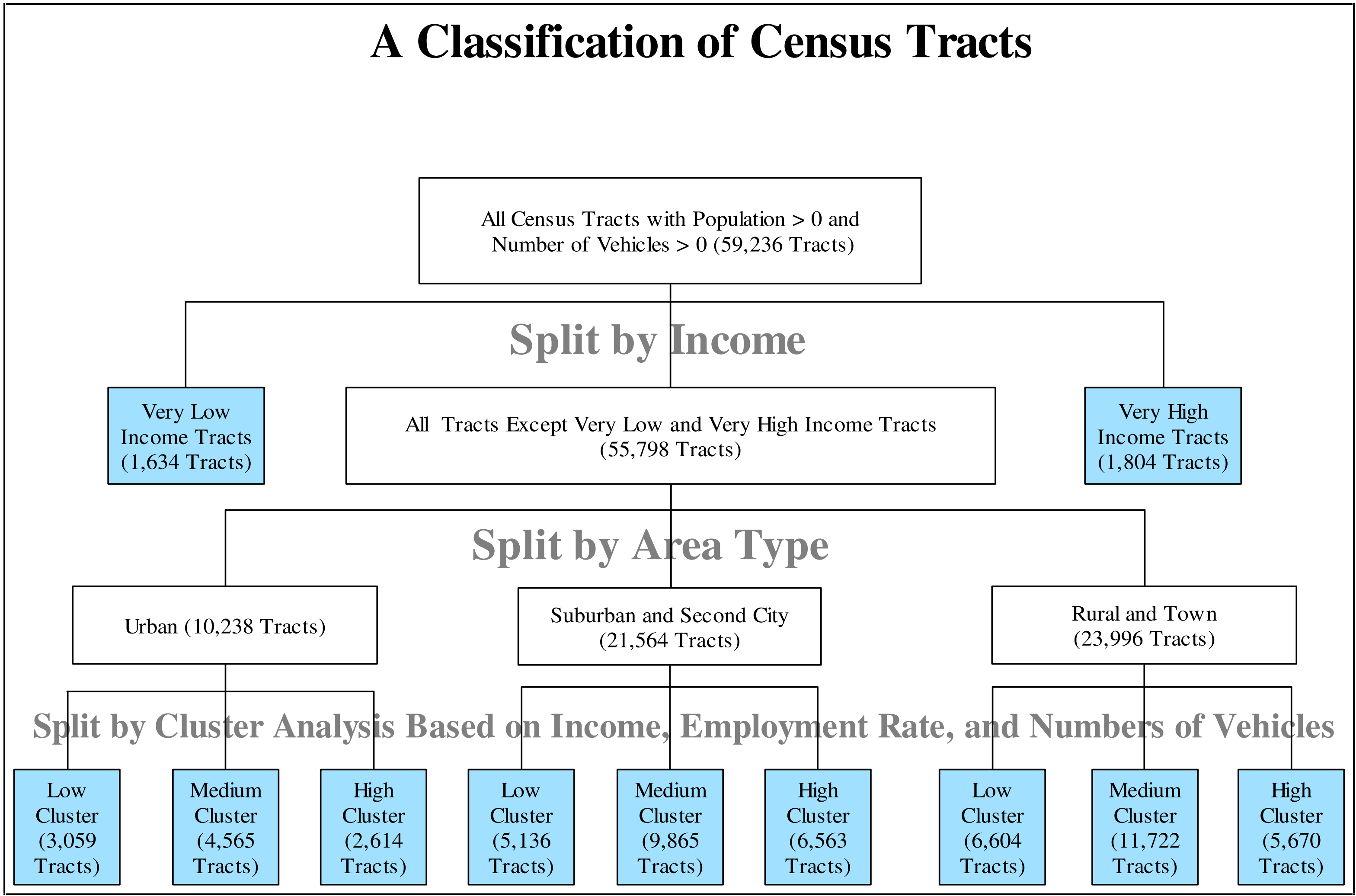

FIGURE 2. Cluster-Specific Differences Between the NPTS and the New York Reserved-Set Data