Day-To-Day Travel Variability in the Commute Atlanta Study

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Submitted to: TRB Committee on Travel Behavior and Values (ADB10)
Paper Number: 07-0538
Date of Submittal: November 15, 2006
Word Count: 5000 words + 4 Tables*250 + 8 Figures *250 = 8000 words

ABSTRACT
Traditional travel diary surveys collect one or two days of travel data from participant households. While cross-sectional travel diary surveys are useful in determining the overall average travel behavior of the regional population, they provide little insight into intra-household and intra-person trip variability. Longitudinal surveys are generally preferred for examining travel variability. The objective of this research effort is to study the intra-household travel variability observed in the Commute Atlanta Study. The Commute Atlanta Study is a GPS-based instrumented vehicle monitoring study that has collected vehicle trips from a fleet of approximately 500 vehicles in 260 representative households. The research effort uses travel data collected in the year 2004 for the Commute Atlanta Study. The average variability or deviation in the number of trips by a household in the Commute Atlanta Study was observed to be 3 trips/day. Demographic variables such as household size, household income, vehicles ownership, number of children, number of workers, and number of students have a significant effect on the day-to-day variability in the total number of household trips per day. The variability due to seasonal effects is controlled by separately analyzing travel data during specific months in the spring, summer, and fall. The analyses found that the demographic variables have a significant effect on day-to-day variability of the household number of trips when the variability associated with seasonal effects is excluded. The researchers noted that vehicles identified by participants as being used always or occasionally for business/commercial purposes undertake very different travel patterns than other vehicles, and that their presence in the sample will significantly bias analytical results in the analysis of longitudinal data. 'Commercial Use' vehicles are excluded from travel variability analysis and the argument is made that households with such vehicles present must be treated as an independent sample in future travel diary data collection and longitudinal studies.

INTRODUCTION

Traditional travel diary surveys collect one or two days of travel data for each household. These traditional surveys do a decent job of capturing average household travel behavior within specific population sectors, when conducted in large numbers using proper random-stratified sampling techniques. However, these traditional surveys do not provide sufficient data for undertaking more detailed behavioral analysis at the disaggregate level [1]. With the evolution of travel behavior analysis and development of more advanced statistical techniques, there appears to be an increased awareness of the need to evaluate day-to-day travel variability at the disaggregate level. Day-to-day travel variability results from the natural daily variation of an individual's transportation needs and desire, and is also affected by feedback from the transportation system (previous travel history, previous experience, congestion levels, etc.). Analysis of day-to-day variability in travel behavior helps travel demand modelers obtain better analytical results using advanced statistical tools, helps social researchers to better understand travel behavior; and helps policy analysts to obtain better insight into the potential effects of transportation policies [2]. Multi-day travel data collected over longer periods in longitudinal studies can provide valuable information for analysis and estimating the microscopic level changes that occur at the household or the person level. The Commute Atlanta Study, an instrumented vehicle study, has collected detailed second-by-second data for more than 1.5 million vehicle trips from 260 households with 480 vehicles over a three-year period. The longitudinal data from this study provide valuable information on intra-household variability of travel behavior. This paper reports the results of one set of analyses recently conducted on the day-to-day variability of household trips/day as a function of various demographic characteristics.

BACKGROUND

Cross Sectional Travel Data

The analysis of cross-sectional travel data assumes that the individual's day-to-day travel is fairly stereotyped, or habitual [3]. The utility maximization theory, which states that the individuals try to perform activities as efficiently as possible, forms the basis of data analysis [4]. In general, the individual tries to satisfy his activity needs rather than optimize his activities, and routine behavior is a stress minimizing satisfying strategy because it eliminates the need for constant decision-making. This leads to the assumption that most people establish habitual behavior patterns. However, many activities of an individual occur in cycles that may be repeated daily, weekly, monthly, or even annually. The cross sectional travel data can present serious problems in drawing inferences from the data due to the temporal variability in travel behavior where potential errors may be associated with the temporal cycle over which an activity occurs.

Cross sectional travel data have analytical limitations with respect to behavioral dynamics in travel behavior [1]:

- Cross sectional data are inadequate to evaluate the response lags and response leads of behavioral adjustments to an event.
- Cross sectional data cannot capture habit persistence, where people exhibit routine behavior even after such behavior is no longer optimal (e.g. habitually shopping at one location even after a closer location with equal utility has opened).

- Cross sectional data are not useful in evaluating threshold or cumulative effects, where the magnitude of change associated with an event needs to be greater or less than a threshold value for behavioral change.
- Cross sectional data cannot evaluate behavioral asymmetry or hysteresis, where people make asymmetric adjustments in behavior in response to symmetrically opposite events.
- Cross sectional data do not capture multiple equilibria, where multiple states of behavior are possible for any set of conditions.

Longitudinal Data

Longitudinal data are important from both policy as well as analytical point of view. Jones and Clarke offer an excellent discussion on the significance and measurement of variability in travel behavior [2]. The emphasis on planning around the world has shifted from capacity expansion to the formulation of transportation policies that effectively manage travel demand, which necessitates better understanding of travel behavior. No matter how big the sample of cross sectional data, it cannot address variations in travel behavior over time. Longitudinal data facilitate the identification of cause and effect relationships as they can account for behavioral dynamics [1]. Longitudinal data are efficient to collect in the case of panel surveys and can provide benefits with respect to survey cost and parameter efficiency. The Puget Sound transportation panel survey, which consists of four waves of travel survey from 1989 to 1993, is a good example of longitudinal data collection using panel surveys. Longitudinal data collected using passive technologies such as instrumented vehicles studies can collect data for a long time without loss in accuracy or participant fatigue.

The longitudinal data and data collection process have their limitations. Longitudinal data, when collected passively, requires state-of-the-art technology and hence highly skilled labor. The turnover of equipment during the course of the data collection can affect efficient data collection. Data collection is also dependant on external services such as wireless and GPS services that may affect the study. The cost of longitudinal data collection is large compared to the cross-sectional data. Longitudinal data collection in both panel surveys and passive instrumented surveys face issues due to subjects leaving the study over time. When passive data collection technology is used, it is difficult to identify trip purpose when a trip ends at a new location. The other significant issue with passive longitudinal data collection is trips made by modes other than auto are not captured.

Variability Studies using Longitudinal Data

Pas and Koppelman examined the determinants of data-to-day variability in individual's urban travel behavior [5]. This paper developed and examined two general hypotheses regarding the determinants of intrapersonal variability in urban travel behavior. The first hypothesis is that individuals with fewer economic and role-related constraints have more intra-personal variability in their daily trip frequency. The second hypothesis tested was that individuals who fulfill personal and household needs and do not require daily participation in out-of-home activities have higher levels of intrapersonal variability in their daily trip frequency. The study tested and verified the two hypotheses to be significant.

Schlich and Axhausen used six-week travel diary data to evaluate habitual travel behavior [4]. The paper found that the day-to-day behavior is more variable if measured with trip-based methods instead of time budget methods. The study observed that travel behavior is neither totally repetitious nor totally variable. The study concluded that the travel period observed should be at least two weeks to measure variability.

Using the same six-week travel diary data as Schlich and Axhausen, Susilo and Kitamura analyzed the day-to-day variability in an individual's action space [6]. This study's results show that out-of-home activity orientation and commitment influence the extension of action space. For workers and students, they observed that the spread of activity locations and the distance to these locations was stable from day-to-day. The study found that random factors have dominant influence on non-workers weekday action spaces and on all individual's weekend action spaces.

The day-to-day variation of individual trip scheduling and route decision for the evening commute was studied by Hatcher and Mahmassani [7]. The detailed 2 week travel diary data from commuters in Austin, TX was used in this study. The study presented models to relate observed route and departure time switching patterns to the commuters' characteristics, such as workplace conditions, socioeconomic attributes, and traffic system characteristics. The study observed high variability of the daily departure time from work, which may be attributed to the trip-scheduling flexibility associated with this trip.

Li, Guensler and Ogle analyzed the morning commute route choice patterns using GPS based vehicle activity data from the Commute Atlanta Study[8]. This study presented a binary logit model for the choice of single route versus multiple route for morning commute based on route characteristics and household's socioeconomic characteristics. The study found that there was a strong relationship between morning commute route choice (single versus multiple routes) and commuters work flexibility, socio-demographic characteristics and commute route attributes.

Commute Atlanta Study

The Commute Atlanta Program is an instrumented vehicle research effort implemented under the Federal Highway Administration (FHWA) Value Pricing Program by Georgia Institute of Technology. The objective of the program is to asses the effects of converting a set of automotive operating costs (gasoline taxes, registration fees, and insurance), into variable per-mile driving costs [9]. The pricing experiments required the collection baseline travel patterns, so that changes in commute, recreation, and social travel associated with pricing could be determined. The research team installed approximately 500 GT Trip Data Collectors in the vehicles of participating households to monitor their driving patterns during the first year with no pricing treatments. A recruiting firm recruited the households randomly to make the sample as close as possible to the demographic distribution of Atlanta. However, due to insufficient number of lower income households volunteering for the study, the sample is biased to the higher income groups. The baseline data included second-by-second vehicle position and speed, as well as engine operating parameters for a subset of vehicles. Household recruitment interviews were conducted with collection of detailed household and personal demographic data followed by a standard two-day travel diary. In addition, project participants routinely received data sheets for submitting changes regarding household and vehicle data. In the second year of the study, households were exposed to a cent/mile pricing experiment designed to simulate the payment of vehicle registration, gasoline taxes, and insurance on a cent/mile basis. Households that reduced their travel activity relative to the baseline year received monetary incentives and households that continued their existing driving patterns received no benefits. The research team monitored a significant reduction in travel during the pricing period and is currently analyzing the data to decouple the effects of experimental pricing and the concurrent, substantial fuel price increase on the travel behavior.

The 2004 Commute Atlanta data represent a full year of baseline travel data for the 263 households recruited to participate in the study. These volunteer household allowed the research team to professionally install a GT Trip Data Collector in each household vehicle driven more than 3,000 miles per year. Using the equipment, researchers remotely monitored the travel patterns of these vehicles, uploading vehicle, and engine operating data via cell phone. The uploaded data are stored in a server and processed to create trip files.

DATA

For the purposes of the travel variability analysis, the research team assembled a subset of the 2004 Commute Atlanta data, which includes all households for which complete travel histories for every primary vehicle in the household were available. That is, if one vehicle experienced an equipment failure and the unit was replaced three weeks later, the household was excluded from the analysis to ensure that all travel data would be captured in the electronic data stream. The Commute Atlanta travel variability data subset includes 153 vehicles representing 98 households. All of the vehicles in these households, with the exception of low-mileage vehicles (under 3,000 miles/year) were installed and all of the tracking devices in the installed vehicles were working properly during the entire baseline year. The use of a full year of data is important to control for seasonal effects of travel variability. Some of these households sold or purchased vehicles during the middle of the year, but the household was included when the researchers were able to directly swap devices from the old to new vehicle. For reasons that will be explained later in the paper, the analyses reported herein also excludes all households that have identified one or more of their vehicles as being used some or all of the time for business/commercial purposes. The research effort defines a child is defined as a person less than 16 years of age as of January 1, 2004.

INTRA-HOUSEHOLD DAY-TO-DAY VARIABILITY

For the 98 households included in the analyses presented herein, Figure 1 shows the average number of trips per day by month. The figure shows the seasonal variation in the average number of trips/day, with a peak in daily trip making occurring at the end of spring.

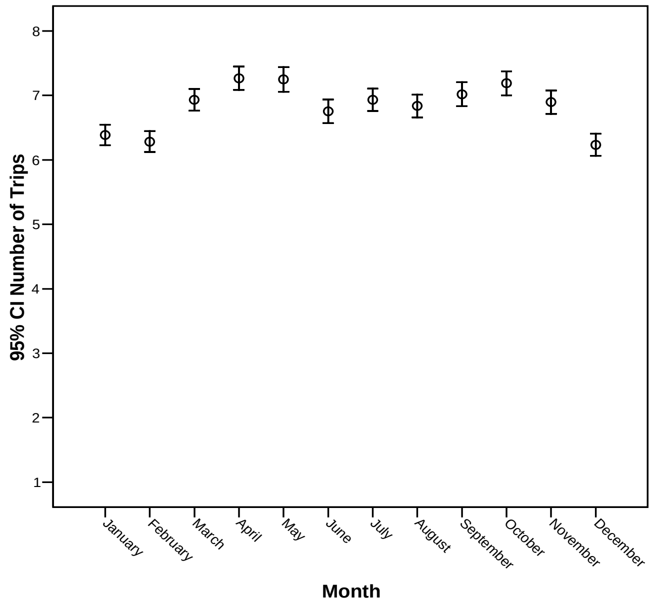

FIGURE 1 Average Number of Trips/day by Month.

Day-to-Day Variability in Number of Trips

The absolute value of the difference between number of trips by a household in a given day and the average number of trips for that household over the entire year is one measure of variability for day-to-day trip making. For the purposes of this report, the deviation will be referred to as "deltatrips." This implies that smaller the value of mean deltatrips the smaller the travel variability for daily household trip making. The deltatrips is not normally distributed because it is the absolute value of the difference. Hence, non-parametric statistical methods are used in this research. The bootstrap method is used in estimating the confidence bounds of the means and Mann Whitney U test is employed to evaluate the differences between two distributions.

Figure 2 summarizes the variation of mean deltatrips by household demographics. The mean deltatrips increases with an increase in number of vehicles in the household and the mean deltatrips are significantly different from each other. The single and two person households have significantly lower variability than the three or more person households. The single and two person households may not have children and that could be the reason for their lower variability. Figure 2 indicates that there is a significant difference in annual travel variability between households that have no children and the households that have at least one child. While one-worker households have similar mean deltatrips to the no worker households, the two worker households have significantly more mean deltatrips. The households with at least one student have more day-to-day travel variability than with households that have no students.

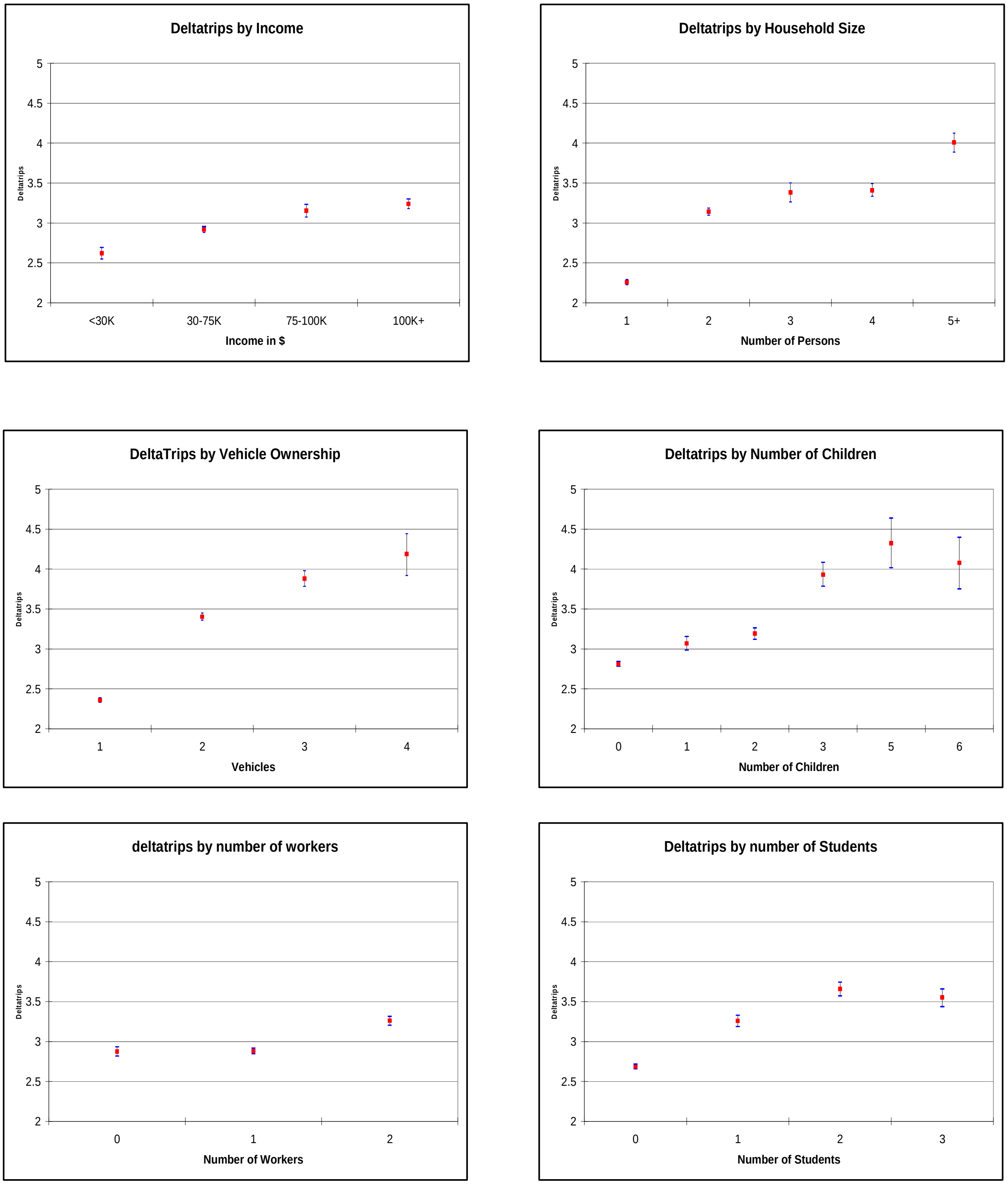

FIGURE 2 Average Annual deltatrips with Confidence Interval (CI) for Households by Vehicle Ownership, Household Size, Income Group, Number of Children, Number of Workers, and Number of Students (N=98 households, for all of 2004).

Hypotheses
Given the above observations, the following hypotheses are tested.

- Hypothesis 1 - Households with higher income levels have significantly more day-to-day travel variability.
- Hypothesis 2 - Households with a single vehicle have significantly less day-to-day travel variability than households with multiple vehicles.
- Hypothesis 3 – Households with no children have significantly different day-to-day travel variability than households with children.
- Hypothesis 4 – Households with no workers have significantly different day-to-day travel variability than households with workers.
- Hypothesis 5 - Households with no students have significantly different day-to-day travel variability than households with students.

Table 1 shows the observed test statistic for the above hypotheses. From the table we can observe that the mean deltatrips is not significantly different for households with income in $75-$100K from households with more than $100K income at 95% confidence. For the low and middle-income groups the test statistic rejects the null hypothesis that the two mean deltatrips are not statistically different at the 95% confidence. The null hypothesis that households with single vehicles have the same mean deltatrips as households with multiple vehicles is rejected (Table 1). The null hypotheses that households with children have the same mean deltatrips as households without children is also rejected. The null hypotheses that households with workers have the same mean deltatrips as households without workers is also rejected. The null hypotheses that households with students have the same mean deltatrips as households without students is also rejected.

TABLE 1 Results of Non-Parametric Tests

Parameter 1	Parameter 2	Mean Rank 1	Mean Rank 2	Mann Whitney U	Significance (p-value)
<$30K	$30-$75K	11153	12043	37394011	0
$75-100K	$30-$75K	11874	12730	40123039	0
$75-100K	$100K+	5986	6069	16645461	0.2*
Single Vehicle HHs	Multiple Vehicle HHs	15630	19963	121420914	0
HHs without children	HHs with children	17316	19254	123954423	0
HHs without workers	HHs with worker	17857	17944	91747152	0.55*
HHs without students	HHs with students	16926	19589	128491149	0
* indicates that the two samples are not different (applies to all tables)					

GT Sample Group
The Commute Atlanta Study recruited households based upon income, household size, and vehicle ownership [7]. The households were classified into eight sample groups called GT sample groups based on income, household size, and vehicle ownership. All households must own at least one vehicle, because the main purpose of the study was to examine the effects of cent/mile and congestion pricing. The first group included all households with income less than

$30K per year, any household size, and any number of vehicles. The second group included all one-person households with an income of $30-$75K and any number of vehicles. The third group included all households with an income of $30-$75K, with at least two persons in the households and only one vehicle. Households in the fourth group have an annual income of $30-$75K, with two persons in the households and at least two vehicles. The fifth group included all households with an income of $30-$75K, with at least three persons in the households and at least two vehicles. The sixth group included households making more than $75K, with only one person in the households and any number of vehicles. The seventh group included all households with an income of $75-$100K, with at least two persons in the households and any number of vehicles. The last group included all households with an income in excess of $100K, with at least two persons in the households and any number of vehicles. This classification enables the analysis of the combined effect of all the three variables.

Figure 3 shows the mean deltatrips by GT sample group, with separate values different number of children in the household. When there are no children in a household, the mean deltatrips is generally lower than for households with multiple children (except for middle-income households with more than two adults). The mean deltatrips increases with the increase in number of adults for households with no children. The mean deltatrips is not significantly different for one-person households with change in income. It is also interesting to note that the middle-income groups shows a decrease in travel variability from one child to two children, and then an increase as additional children are present. This may be associated with family structure and lifecycle stage of the family (i.e. the relative ages of the children significantly affect the household travel demands). The research team will be examining this effect during the case study development for household pricing response.

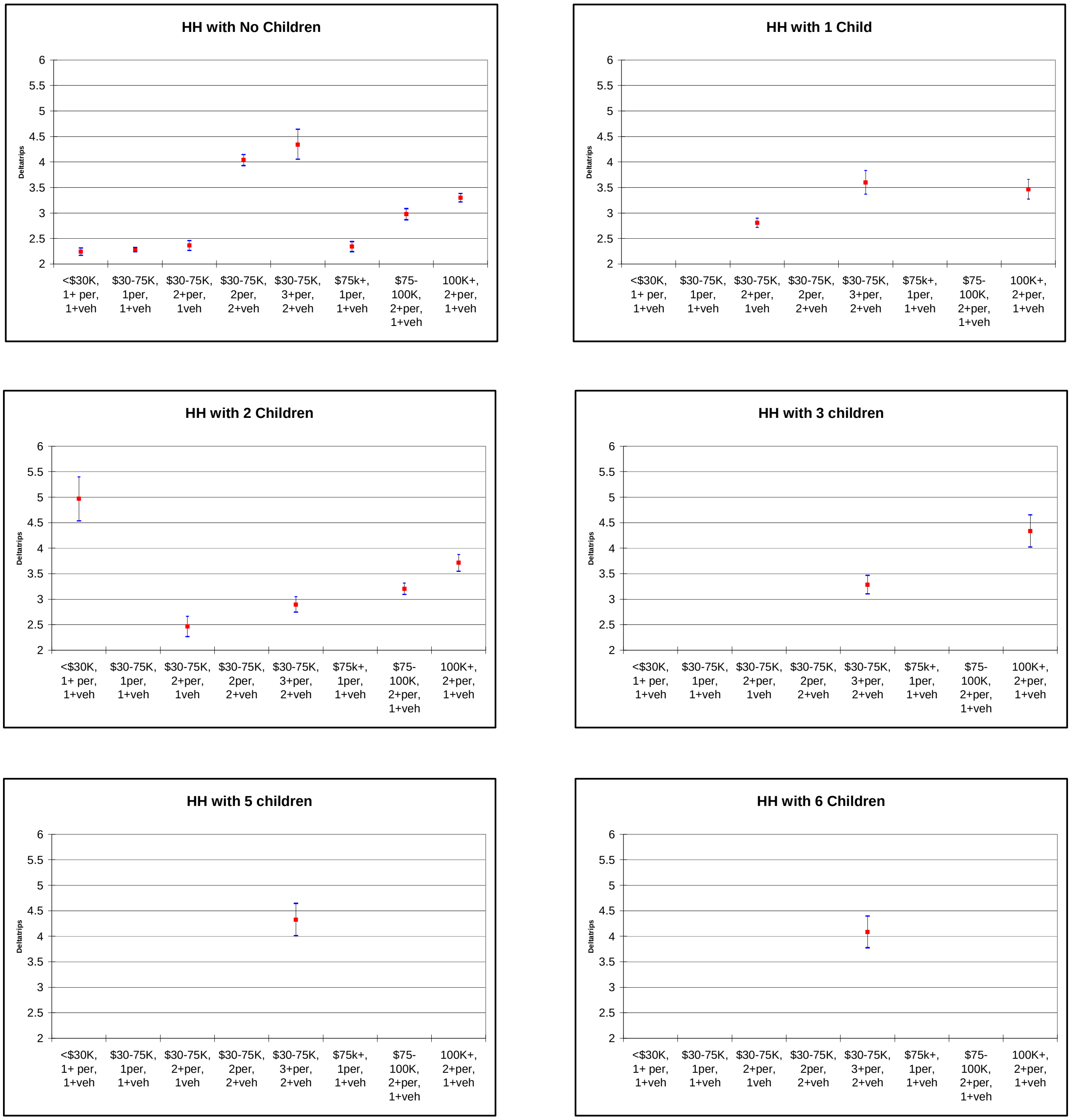

FIGURE 3 Mean Deltatrips by GTSample Group and Number of Children.

Variability by Day of Week

Figure 4 shows the mean deltatrips by day of week. The mean deltatrips for weekdays is consistent from Monday to Thursday and slightly higher on Friday. During weekdays, trip making may be more habitual, with less variability as expected. The greatest variability in mean deltatrips is noted on Saturday. Many social engagements and shopping activities happen over the weekend, starting Friday evening, and especially on Saturdays. The trips produced by these social activities are more likely to be non-habitual and vary even from week to week. Therefore, the high variability on weekends and especially on Saturday is as expected.

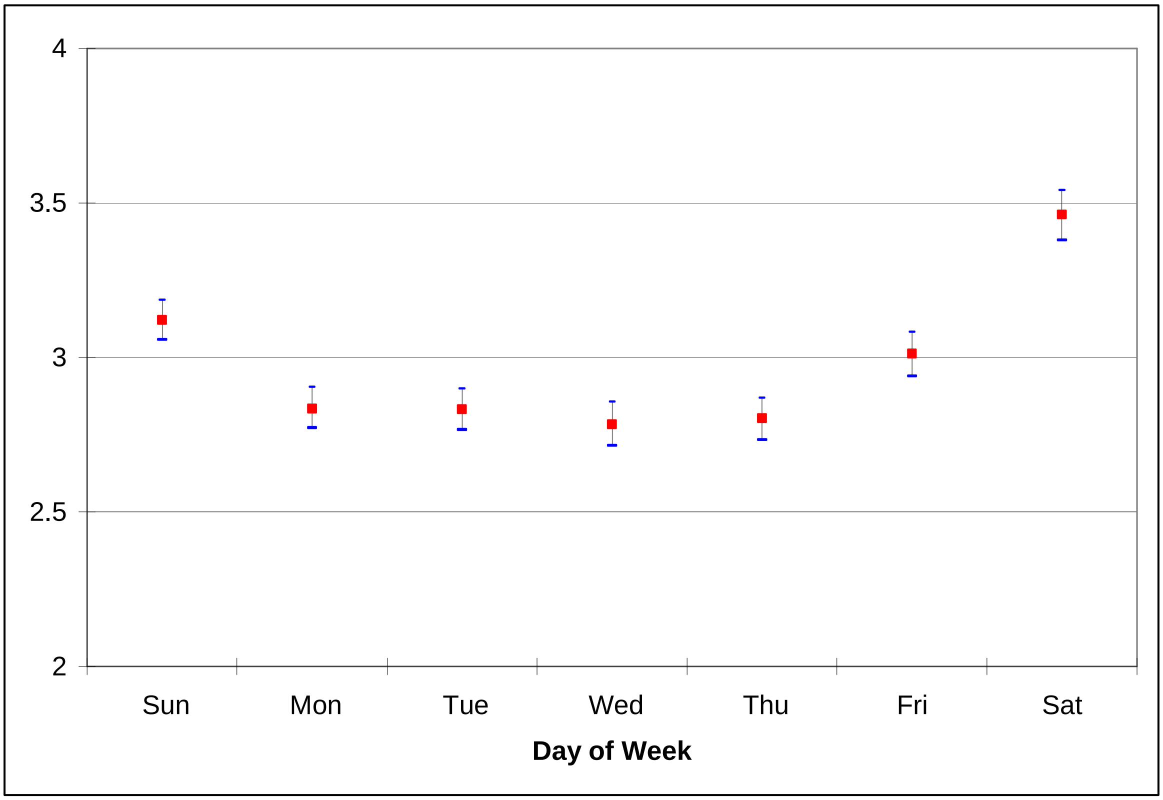

FIGURE 4 Mean deltatrips by day of week.

Day-to-Day Variability in Spring
Seasonal effects have significant impact on the number of trips per day as was noted in Figure 1. To evaluate day-to-day travel variability excluding seasonal effects, the analysis is performed on a 31-day period in spring (March 15, 2004 to April 14, 2004). The deltatrips for this analysis is the deviation of the day's trip from the mean number of trips during the analysis period.

Figure 5 shows the day-to-day travel variability for the spring travel data. The household mean deltatrips has significant differences between single vehicle households and multi vehicle households. However, the difference in deltatrips among the different number of vehicles in the multi vehicle households is not significant. While the general trends in Figure 5 are similar to the trends in the full year analysis shown in Figure 2, we find that the mean deltatrips are closer to each other in the spring analysis than in the full year analysis. The households with no children do not have significantly different deltatrips than households with children. There is also no significant difference in the mean deltatrips of households with 1, 2, 3, 5 or 6 children

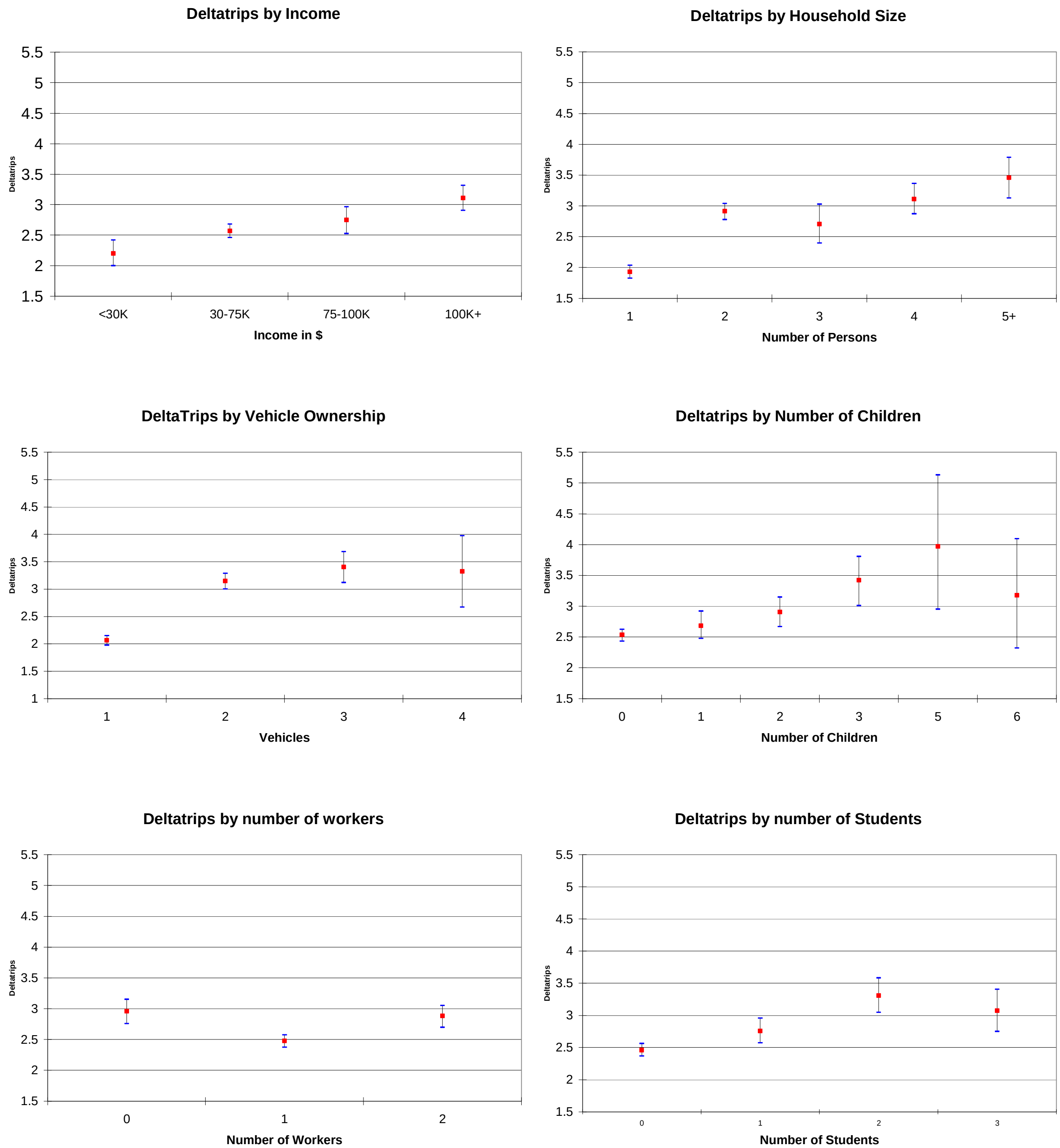

FIGURE 5 Average deltatrips with Confidence Interval (CI) for Households in Spring by Vehicle Ownership, Household Size, Household Income, Number of Children, Number of Workers and Number of Students (n=98 households).

TABLE 2 Results of Non-Parametric Tests for Spring Data

Parameter 1	Parameter 2	Mean rank 1	Mean Rank 2	Mann Whitney U	Significance (p-value)
<$30K	$30-$75K	925	1024	257116	0.004
$75-100K	$30-$75K	1011	1075	292066	0.061*
$75-100K	$100K+	495	521	115030	0.183*
Single Vehicle HHs	Multiple Vehicle HHs	1308	1706	847928	0
HHs without children	HHs with children	1463	1641	880709	0
HHs without workers	HHs with worker	1644	1493	595807	0
HHs without students	HHs with students	1439	1652	932425	0

The same set of hypotheses tests for the full year data are tested for the spring data. In the spring data, the null hypothesis that the mean number of deltrips between middle income and high-income groups are the same is not rejected. The null hypothesis that households with single vehicles have the same mean deltatrips as households with multiple vehicles is rejected from table 2. The null hypotheses that households with children, workers, and students have the same mean deltatrips as households without children, workers, and students respectively are rejected. From the above tests, we can argue that the general trends of full year's travel variability are likely to also be observed in spring travel data variability.

Day-To-Day Travel Variability in Summer

More households take vacations in summer, and schools are usually not in session, therefore summer travel is typically different from the rest of the year. The analysis period for summer should exclude holiday traveling period such as Independence Day to remove large variations in travel patterns. The analysis period chosen for summer analysis is July 15, 2004 to August 14, 2004. Figure 6 shows the day-to-day variability analysis for the summer travel data.

From figure 6, we can observe that summer travel variability exhibits some differences from the full year variability as well as spring variability. While household vehicle ownership follows the general trends, the household size group variable is quite different. Except for the one-person households, the household sizes do not have a significant difference in the mean deltatrips. The difference in the mean deltatrips for single person households compared to others maybe due to single person households not being involving in as many summer social and recreational activities, in which multi person households participate. The lower income group has significantly different mean deltatrips from the other groups, while the other groups have no significant difference. It is possible that lower income households (that own vehicles) are less likely to engage in recreational activities requiring travel as compared to middle and high-income groups, which might explain the observation. In the summer, households with children have multiple activities, which usually do not occur during the rest of the year, such as special day and overnight camps. Households with children have higher variability in their day-to-day trips in summer compared to the full year or spring, which may be due to these new activities. The variability across the number of students in the household follows the same trend as the number of children. From the above analysis, we can observe that variability in summer is different from the variability in annual travel and the spring season travel.

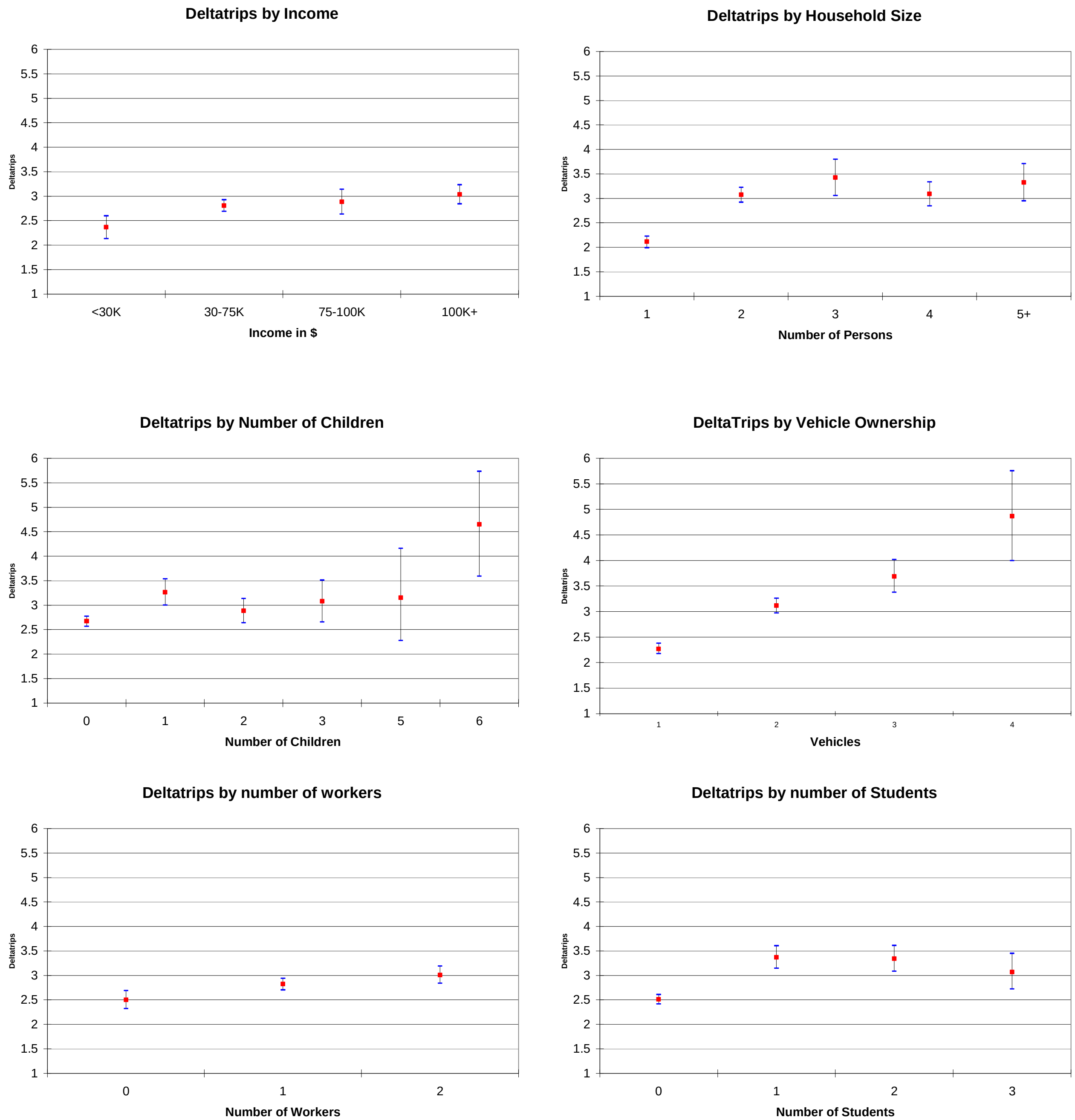

FIGURE 6 Average deltatrips with Confidence Interval (CI) for Households in Summer by Vehicle Ownership, Household Size, Household Income, Number of Children, Number of Workers and Number of Students (n=98 Households).

Table 3 shows the results of the test statistic for this hypothesis testing. The null hypothesis that different income groups have the same deltrips is not rejected except for the lower income group. The other hypotheses are in line with the general trends observed in the full year's data and spring data and reject the null hypotheses.

TABLE 3 Results of Non-Parametric tests for Summer Data

Parameter 1	Parameter 2	Mean rank 1	Mean Rank 2	Mann Whitney U	Significance (p-value)
<$30K	$30-$75K	923	1025	256490	0.003
$75-100K	$30-$75K	1018	1044	303703	0.457*
$75-100K	$100K+	499	519	116513	0.314*
Single Vehicle HHs	Multiple Vehicle HHs	1350	1669	908282	0
HHs without children	HHs with children	1464	1639	882758	0
HHs without workers	HHs with worker	1451	1533	625556	0.049
HHs without students	HHs with students	1414	1692	886290	0

Day-to-Day Travel Variability in Fall

A Fall travel data period was selected to avoid the holiday season, where increased shopping activities can have a large effect on variations in travel behavior. The selected period for fall data was October 1, 2004 to October 31, 2004. Figure 7 shows the travel variability observed in the Fall travel data.

In Figure 7, fall travel variability is similar to the general trends seen in the full year travel variability analysis presented in Figure 2 and the Spring travel variability analysis presented in Figure 5. The difference in the mean deltatrips across income groups is not significantly different, except for the low-income households.

Table 4 shows the results of the test statistic for this hypothesis testing. The null hypothesis that different income groups have the same deltrips as other is not rejected, except for the lower income group. The null hypothesis that households with workers have the same deltrips as households that do not is not rejected The other hypotheses are in line with the general trends observed in the full year's data and spring data.

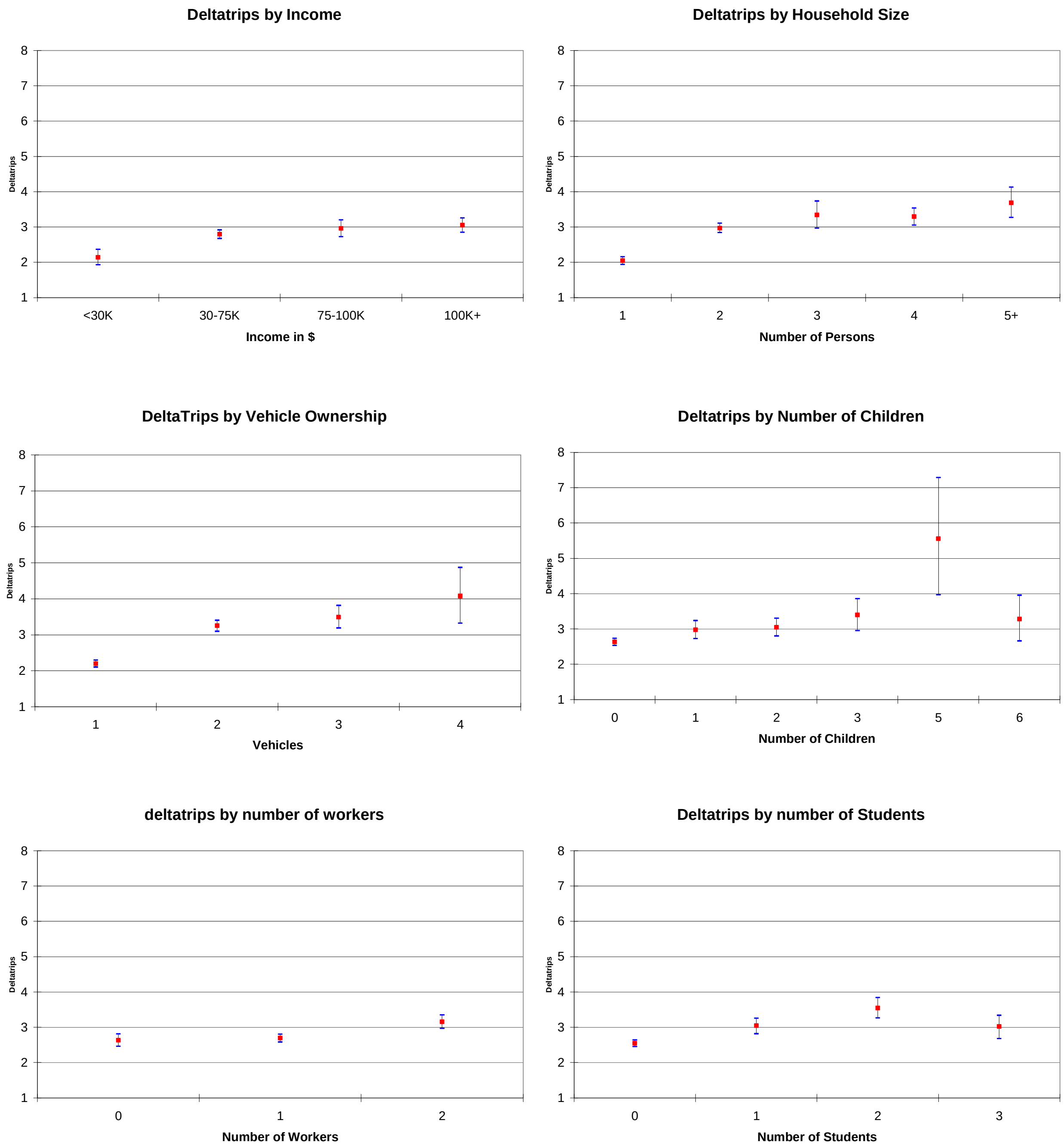

FIGURE 7 Average deltatrips with Confidence Interval (CI) for Households in Fall by Vehicle Ownership, Household Size, Household Income, Number of Children, Number of Workers and Number of Students (n=98 households).

TABLE 4 Results of Paired T-test for Fall Data

Parameter 1	Parameter 2	Mean rank 1	Mean Rank 2	Mann Whitney U	Significance (p-value)
<$30K	$30-$75K	890	1032	245188	0
$75-100K	$30-$75K	1004	1111	278775	0
$75-100K	$100K+	516	509	119457	0.72*
Single Vehicle HHs	Multiple Vehicle HHs	1328	1688	877401	0
HHs without children	HHs with children	1464	1638	883877	0
HHs without workers	HHs with worker	1496	1524	649322	0.5*
HHs without students	HHs with students	1440	1649	935688	0

Effect of Commercial Vehicles in Day-to-Day Variability

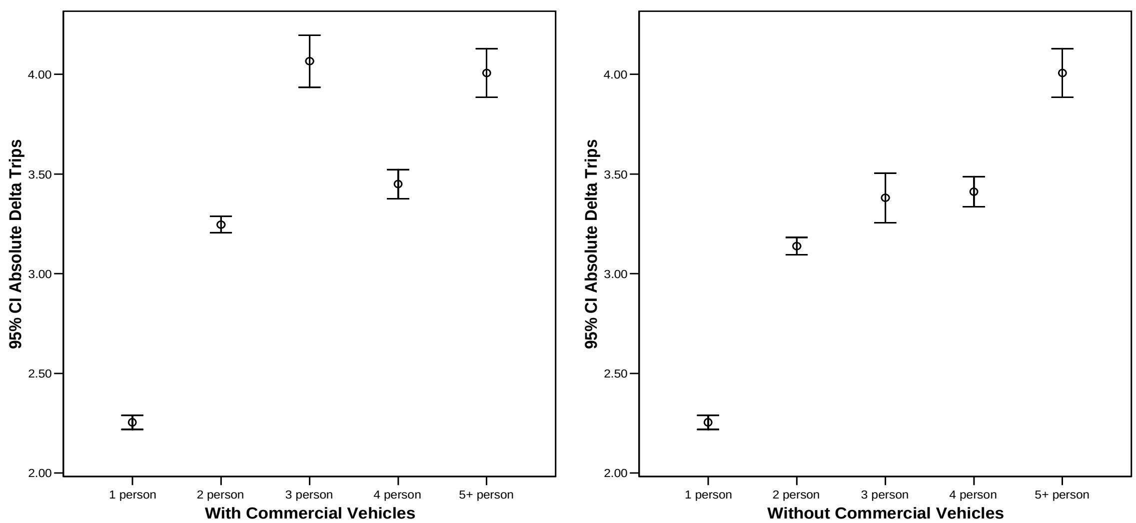

FIGURE 8 Effect of Commercial Vehicle on Household Size Analysis.

Early in the paper, the authors asserted that commercial vehicles need to be excluded from the variability analyses. The effect of commercial vehicles on the Commute Atlanta longitudinal data is significant. Commercial vehicles are vehicles, which the households claim to use for commercial purposes, during the household survey. The households Figure 8 shows the effect when commercial vehicles are left in the dataset on the mean deltatrips by household size. The 3-person household group's mean delta trips decreases significantly when commercial vehicles are not included in the analysis. This is because the ownership of commercial use vehicles is not uniform across the household size groups, and there are potential interactions between the presence of the commercial use vehicle and the household travel data as a function of household size (and family lifecycle stage interacting with employment type). The same kinds of potential biases in analytical results were noted across a wide variety of analyses conducted to date by the research team. Hence, it is essential to ensure that commercial vehicles do not bias the analysis in longitudinal travel data.

CONCLUSIONS

The research effort studied the number of household trips variability against the demographic characteristics of the households. The variability in the number of household trips arises due to seasonal, temporal, and non-habitual activities. Research results indicated that households with higher income, larger households, households owning a greater number of vehicles, households with children, and households with students have significantly higher variation in the number of trips per day. The results seem logical, given that these household types may need to make more trips and participate in more non-habitual activities. To control for seasonal effects, the researchers looked at travel variability within one-month periods for Spring, Fall, and Summer. The variability in trip making by demographic factor for spring and fall was similar to that of the full year's variability. Analysis of summer travel data, however, indicated that only lower income households, single person households, and households with no children (which generally exhibit significantly lower annual variability than other groups) exhibited no significant difference between annual and summer variability. Summer variability in travel increased significantly across the other demographic groups. The research effort would also like to underline the importance of dealing with commercial vehicles in longitudinal data since their presence in the data set can significantly bias variability results and yield counter-intuitive results.

The Commute Atlanta Study has collected unique longitudinal data over the last 3 years. The data are collected passively using vehicle instrumentation. Hence, the data do not suffer errors due to survey fatigue and non-reporting of trips over the duration of the study. The research into travel variability in time and space using the Commute Atlanta data is ongoing. The next sets of analyses are focusing on variability in travel activity in time and space by trip type. Given the relatively small longitudinal sample size, a case study approach is being used for these forthcoming analyses. However, given the results to date, the researchers are confident that future research efforts using larger instrumented vehicle samples will be able to provide very useful data on travel variability for use in activity-based travel demand model development

ACKNOWLEDGEMENTS
The research presented in this paper is part of the Commute Atlanta Study, funded by the Federal Highway Administration's Value Pricing Program and the Georgia Department of Transportation.

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