An Analysis of Morning Commute Route Choice Patterns Using GPS Based Vehicle Activity Data

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ABSTRACT

This paper examines the morning commute route choice behavior of 182 drivers, using disaggregated GPS-based activity data collected during a ten-day period. This paper attempts to describe how these commuters tend to behave in the real world. A binary logit model of morning commuters' choice between using a single commute route and multiple routes was established, based upon the evidence of drivers' varying valuations of a number of route and trip characteristics as well as the commuters' socio-demographic characteristics. The research results of this paper indicate a strong relationship between the morning commute trip-chaining decision (single vs. multiple routes) and work schedule flexibility as well as commuters' socio-demographic characteristics and commute route attributes. Understanding travelers' route choice behavior can help in designing route choice algorithms that are based upon more realistic assumptions.

INTRODUCTION

Urban commute trips have been of significant interest to transportation researchers, given the fact that the journey-to-work temporal peak places great strain on the urban transportation system. For most commuters, the work trip is often the longest daily journey. As traffic congestion has long been a common phenomenon in large metropolitan areas, it is a major source of frustration for a large percentage of commuters (1). In response to congestion, whether recurring due to capacity constraints or sporadic due to traffic incidents, commuters are likely to adopt different strategies to avoid congestion and minimize commute time. Due to the nondiscretionary nature of the commute trip, departure time and route selection constitute the primary choices available to commuters on a daily basis. In contrast, the time-frames for decisions of mode shifts, telecommuting, residence relocation, and change of work place are comparatively longer.

The problem of route choice faced by an automobile driver is very complex. First, there can be a large number of possible alternative routes through the road network from origins to destinations, and complex patterns of overlap typically exist between the various route alternatives (2). The ultimate route choice decision results from the consideration of both socioeconomic and trip characteristics. Important factors in the travelers' socioeconomic characteristics may be age, gender, income, personality, habits, preference, driving experience, and familiarity with the transportation network. Trip characteristics include trip purpose, time and location, flexibility in arrival time, availability of alternative routes, traffic conditions, and traffic information that influence travelers' decision both before the trip and en-route (see Jan, et al. (3)).

The decision making process of route choice is also a dynamic process. A learning process is central to the driver's cognition as the information acquired through experience of earlier travel choices is processed before the next decision is made. Moreover, the characteristics of each known alternative route do not have the same importance in a driver's final decision. On the basis of a factor importance hierarchy, the traveler formulates a choice set of sufficiently attractive alternatives. From this set, travelers make their choices, with the chosen route being the one that best satisfies their needs and are consistent with their personal constraints and preferences. Finally, inertia also plays a role in choice behavior, dictating that certain thresholds are crossed before drivers change their habitual behavior (4).

Although a variety of research efforts have focused on route choice behavior, actual route choice behavior on real-world highway networks has not been adequately investigated due to a lack of sufficient observational data. This paper examines the choice between the utilization of single and multiple routes for the morning commute based on the disaggregated observations of 182 drivers collected using GPS in-vehicle data recorders during a ten-day period and attempts to describe how commuters behave in a real world situation. Understanding travelers' route choice behavior in real world can help to redesign route choice algorithms that are based upon more realistic assumptions.

This paper is organized into five sections. Section two summarizes related literature. Section three presents data collection methods, and describes the data source and sample statistics. Section four describes the modeling methodologies and model specifications. This section also presents the empirical results of the models and the effects of the explanatory variables. The final section provides a summary of the research findings, and identifies possible extensions of the research.

LITERATURE REVIEW

Extensive research has been carried out in the area of route choice. Previous research established theories of route choice decision-making process (2,5,6,7,8,9) and identified route choice factors other than travel time and distance (2,3,7,10). Most recently, a large number of research efforts have been devoted to studying the route choice behavior under the influence of traffic information system (8, 11, 12, 13), the dynamic aspect of the route choice behavior, and the interrelation of route choice, departure time, and trip-chaining decisions.

In the survey carried out by Abdel-Aty et al. (14) in the Los Angeles area in 1992, only 15.5 percent of the respondents said they used more than one route to work. The most frequent reason for changing routes, cited by 34 percent of respondents, was the traffic that the respondents saw on the roads. Individuals with higher incomes or higher education levels tend to report using more than one route to work.

Mannering (1) used a Poisson regression to predict the frequency of commuters' route changes per month. He found out that both highway network (e.g. the availability of alternative routes, travel time on the primary route, the level of traffic congestion) and commuters' socioeconomic characteristics played important roles in the frequency of route changes. As commuter age increases, fewer route changes are made. Unmarried people were found to be more likely to change routes than their married counterparts. Male commuters were found to be more likely than females to change routes. These findings may reflect more risk-seeking or impatient behavior among single commuters, or simply capture the fact that married commuters may be constrained by spousal carpooling, school/day care drop-offs and pick-ups, or other family-related responsibilities.

Mannering and Kim (15) collected survey data from Interstate 5 (I-5) commuters in the Seattle metropolitan area and used an ordered logit model to predict the frequency of changing home-to-work routes. Examining specific coefficient estimates, they found that the longer the daily commute time, the higher the frequency of route changes. Commuters indicating that they had considerable flexibility in departure times at home and at work were found to be more frequent route changers. Furthermore, the greater the commuters' familiarity with alternative routes, the higher the frequency of route changes. Turning to socioeconomic variables, they found men were more likely to change routes than women, and individuals with low incomes were found to be less likely to change routes frequently.

Mahmassani et al. performed a survey of commuters in Austin, Texas (16) and yielded a binary logit model that relates route switching propensity to four types of factors: geographic and network condition variables, workplace characteristics, individual attributes, and use of information (radio traffic reports). They found that those variables describing the characteristics of the commute itself had a dominant effect relative to workplace rules or individual characteristics. The use of information in the form of radio traffic reports also appeared to exert a strong effect. Regular listeners to traffic reports had a greater propensity to switch routes. The only socio-demographic attribute included in the model was age.

Jan et al. (3) concluded that GPS is a viable tool to study travelers' route choice patterns. GPS data collection methods can reveal important travel behavior information that was impossible to discern with earlier conventional survey methods. They found that travelers habitually followed the same path for the same trip. However, path deviation increases as origins and destinations become farther apart.

From the review of the literature, most of the research results reported for route choice are based upon stated preference surveys or simulation methods. Few studies were based on revealed preference surveys, and very little work has been done based on the field observation method. Recent developments in GIS provide handy tools to manage the large amount of spatial related data captured by GPS units and to post processing to attract route choice information from the raw GPS data. A study based on the real world observations of the actual behavior can help developing a larger body of knowledge in route choice.

DATA DESCRIPTION

The commute behavior data used in this paper are field observations collected in an ongoing in-vehicle activity data collection effort known as Commute Atlanta. The Commute Atlanta program is an instrumented vehicle research program funded by the Federal Highway Administrations (FHWA) Value Pricing Program and the Georgia Department of Transportation. The project deployed instrumentation in 487 vehicles from 268 representative households in the 13-county Atlanta metro area and has collected second-by-second speed and position data for more than 600,000 trips during the first ten months of data collection.

The GT Trip Data Collector is the in-vehicle Event Data Recorder (EDR) used in the study. Figure 1 shows the outside of the EDR and Figure 2 shows the EDR with wiring harness and accessories. Major components of the EDR include CPU, power supply, cellular transceiver, GPS, and other sensors. The optional connections connecting to the EDR include six on/off sensors and two serial connections. These sensors can detect seatbelt usage, ODB data, braking, windshield wiper etc. The EDR turns on and off automatically with the vehicle ignition. Hence no human input is required. These features make the EDR a practical option to monitor travel behavior 24 hours a day during multi-day period. The Commute Atlanta project data collection system map is shown in Figure 3. The digital cellular transceiver is capable of sending data through low cost short message service (SMS) or sending larger volume circuit switched data.

To extract related information from the raw GPS-based vehicle activity dataset, the authors developed a series Perl scripts to capture morning commute travel information including start and end time, commute duration, travel time and distance, and trip-chaining behavior. The authors also developed a map matching procedure using Arcinfo^{TM} AML to translate the participant's location onto the GIS digital road network and hence extract the traveled route. Another script was developed to compare the different routes utilized by the same driver based on the shared link distance. Minor deviations around the neighborhood streets close to trip ends, or a 'rat run' to avoid an intersection at a network node, are not counted as a route change.

Although at the time when the paper was prepared, the project has collected around one-year worth of travel behavior data in raw format, generating a full data set in the format that is ready for analysis involves a large amount of data processing and data mining efforts. Hence, a subset of ten-day's worth of morning commute journeys for 182 drivers from 138 households was used in this paper. The number of drivers is mainly restricted by the criteria of vehicle sharing and employment status. In the Commute Atlanta research, every instrumented vehicle has one associated primary driver. In this paper, only the drivers who work full time or part time at a fixed work location who do not share the vehicle with another member in the household are included. The 10-day observation duration was selected to capture some repetitive behavior from week to week. Due to the fact that a certain driver may not necessarily work all five work days and the driver may occasionally use a travel mode other than drive alone by primary vehicle, the 10-day period does not necessarily represent 2 complete work weeks (Monday through Friday). The household travel survey has the home address of each household and the work address of each worker in the household in latitude and longitude format. A series of trips with the first trip starting at home, the last trip ending at the work place, and all trips intermediate, that take place during the morning commute time-period on a given day are considered a single morning journey-to-work. The morning commute time period was defined as 5 a.m. to 10 a.m. local time Monday through Friday. Vehicle activities that occurred on public holidays were excluded from the dataset.

A rich source of individual and household data has been collected in the household travel survey. The average age of the sample is 43 years. Most of the drivers have resided at their current residence location for more than 3 years, indicating a good level of familiarity with the network conditions. The respondents are divided fairly equally between males and females with 49.5 percent being males. The ratio of workers per household is 1.45, which is comparable to 1.37 from the Census 2000 data for Atlanta MSA. Household vehicle ownership of the sample is higher than the average value of Census 2000 for the Atlanta MSA. The sample has 2.37 vehicles per household compared to the 1.8 vehicles per household of Census 2000. At least 55 percent of the drivers have either undergraduate or postgraduate qualifications. The median household income of the sample is between \$75000 and \$99000. The value is significantly higher than the median household income of the Atlanta MSA (\$51948 in year 2000 Census). While the higher values are partly due to overall Commute Atlanta household recruitment (discussed in the next paragraph), it is important to keep in mind that this sub-sample is of working commuters that are included in the larger Commute Atlanta household sample.

The household recruitment strata in the Commute Atlanta study are based on annual household income, household size and vehicle ownership. The Commute Atlanta samples are slightly skewed to the higher income groups comparing to the Atlanta population due to the restrictions in vehicle ownership and vehicle sharing. This difference is expected since the objective of the Commute Atlanta project is designed to access the effects of by-the-mile congestion pricing on commute travel behavior, and only households that own vehicles were recruited. The researchers also found out that higher-than-expected refusals and opt-outs of lower income households and higher-than-expected retention of upper income households. In the Commute Atlanta project, participants are not monetarily incentivized to participate, but the monitoring devices provide participants with vehicle theft tracking capabilities. Upper income households may have also placed a higher value on the Commute Atlanta project objectives (specifically on the identification of congestion locations). Details on the recruitment process and study refusal rates are detailed in Ogle, et al. (17,18).

The participating commuters employed in the analyses reported here have higher than average incomes. This results in part from the overall higher income household participation in the study, coupled with the demographics of commuters in general (i.e. commuters with white collar occupations usually have higher salary and a fixed work schedule that involves a peak period commute). Lower income commuters may work shifts that fall outside of the traditional morning and afternoon peak commute times. Hence household income values for the commuters identified during the morning peak periods are higher than the overall working population. The net result, however, is that upper-income households and more educated individuals are over-represented in the sample when compared to census demographic profiles of the Atlanta Metropolitan Statistical Area (MSA) population. Hence, conclusions regarding behavior with demographics need to be restricted to each sample strata where sufficient data are available.

In the sample, around 40 percent of the commuters used only one route for their commute during the 10-day period. The remaining 60 percent of the commuters used at least two routes for commute. Researchers defined routes that have been utilized at least twice by the same driver during the study period as routine routes. Approximately 33 percent of the commuters have at least two routine routes. These values are higher than those reported by Abdel-Aty et al. (14), in which only 15.5 percent of the respondents said they used more than one route to work. Table 1 summarizes the distribution of morning commute routes.

METHODOLOGICAL APPROACH

To assess the commute route choice dynamics during the study period, a binary logit model of commuters' route choice decision was developed for use of a single route vs. multiple routes. The dependent variable has binary outcomes that indicate whether a commuter used a single route or multiple routes during the 10-day period. The model developed in this paper is based on the evidence of drivers' valuations of a number of route and trip characteristics as well as the commuters' socio-demographic characteristics.

Model Specification

Table 2 provides a list of independent variables used in the model, their definitions, and associated descriptive statistics in the sample. Three categories of the explanatory variables that influence a commuter's route choice propensity, including commute information, primary route attributes, and commuters' socio-demographic information, are included in the empirical analysis. Although a model specification that accounts for the cognitive learning process and access / acquisition of information should be more accurate, such information is not available in the current data set.

- **Individual and Household Socio-demographics**

This group of variables is designed to account for the taste variations in choices between different population groups, as well as to capture the effects of the life-cycle stage of a household on route choice behavior. This group of variables includes commuter's age, gender, education level, household size and income, residence type, and tenure at residence. Cut-off points for age and income dummy variables were created using tree model analysis based on deviation minimization. The group of commuters with household annual income less than $100,000 is set as the reference group for the income dummy. One dummy variable is used for commuters with household income greater than or equal to $100,000. The group of commuters with age between 45 and 52 is set as the reference group for age groups. Two dummy variables are used for age group. One dummy variable is for the group of age less than 45, and another is for the group of age higher than 52.

- **Commute Journey Attributes**

This group of variables is designed to capture the impact of work schedule flexibility and trip-chaining on commuters' route choice. Two schedule flexibility variables are developed to reflect the workers' ability to vary their arrival and departure times. The number of commute journeys whose departure times vary less than 5 minutes before or after the median departure time of the ten-day period (Dless5) is chosen to represent departure time inflexibility. The number of commute journeys whose arrival times vary more than 30 minutes before or after the median arrival time of the ten-day period (A30more) represents the arrival time flexibility. Trip-chaining frequency is represented by the number of trip-chaining stops made during the 10-day period.

- **Primary Route Characteristics**

A primary route is the route that a commuter uses most frequently during the study period. This group of variables tries to capture the impact of the primary route's traffic condition and driving experience on commuters' decision making. This group of variables includes commute time and distance, average travel speed, number of idle stops, percent of freeways, and number of traffic signal. In this paper, commute duration is defined as the total time elapsed between the time point when the driver turns on the vehicle engine and leaves home and the time point when he/she turns off the vehicle engine at the work place. Travel duration equals the commute duration minus all the trip-chaining stop durations during that commute journey. Travel distance is calculated by accumulating the second-by-second linear distance between two consecutive GPS points. Objective road characteristics, such as roadway functional classification and traffic controls, are based on the Georgia Department of Transportation (GDOT) Road Characteristics (RC) database for year 2000. Based on the GPS vehicle activity data, the number of idle stops is defined as the number of periods during the commute journey when the vehicle is traveling on the road network at a speed less than 5 mph for at least one minute duration. The variable is designed to catch the traffic volatility and driving experience on a certain route. A route with more traffic signals, stop signs and other traffic control devices, or a route is more congested may have larger number of idle stops.

The reliability of a particular route can be expected to play an important role in the traveler's decision of whether using a secondary route. Travel time standard deviation was proposed to investigate the effect of travel time variability, but due to the small number of observations per route, the travel time standard deviation cannot be taken as a representative value of the travel time variation of a certain commute route. Therefore, it was not included in further model development. Free flow travel time is calculated based on link distance and free flow travel speed of different road functional classes from the Atlanta Regional Commission's transportation planning model. A ratio between the real travel time and the free flow travel time was calculated to represent the congestion level of the primary route, but this variable was not statistically significant in any of the models discussed later. Hence, it is not included in model estimation.

The choice of variables for potential inclusion in the model was guided by previous theoretical and empirical work on route choice modeling. The final specification is based on a systematic process of eliminating variables found not to be statistically significant in previous specifications and based on considerations of parsimony in representation. Some variables with marginally significant coefficients are retained in the final specification, either for the sake of completeness or because they provide useful and suggestive insights. The univariable models show that among the primary route attributes, average travel speed, percentage of freeway travel distance, and the number-of -signals have marginal impact on the dependent variable; among the socio-demographic variables, gender, residence type and tenure at residence have marginal impact on the dependent variable. Hence, they are excluded in further model development.

Model Estimation

A correlation matrix was computed to detect potential collinearity between all pairs of the explanatory variables included in model estimation. The resulting correlation coefficients are all less than 0.60, which indicates there is no unacceptable correlation between any two specific variables (Table 3).

The final model specifications and parameter estimation results are presented in Table 4. The first model uses only commute journey information. The second model uses only primary route characteristics. The third model uses only driver and household socio-demographic attributes. The final model uses all three groups of explanatory variables. All of the coefficient estimates have the expected signs. Since the coefficient determines the probability that a commuter uses multiple routes, a positive coefficient for a variable means that the probability of using multiple routes increases with the increase in the value of that variable. All of the individual coefficient estimates for the first three models, except for the distance variable, are significantly different from zero at the 90 percent confidence level. In the fourth model, all the variables in the first three models are included. The variables including A30more, trip-chaining and dummy for age group younger than 45, are significantly different from zero at the 95 percent confidence level.

Of the three categories of variables discussed in the previous section (commute characteristics, individual attributes, primary route attributes), those that describe the characteristics of the commute itself have a dominant effect relative to the other two independent variable categories. This result is consistent with the research result of Mahmassani et al. (16) in which route switching propensity was developed from a commuting survey of 638 households.

Effect of the Explanatory Variables

Changes in the predicted probabilities of using multiple commute routes based upon the changes of the independent variables in model 4 are listed in Table 5. Model 4 indicates that among the commute information variables, trip-chaining behavior and work schedule flexibility increase drivers' propensity of choosing multiple commute routes. The probability of having multiple commute routes is higher for people who make stops during their morning commute than for those who do not make stops. Li et al. (19) also found similar relationship in the observation of 56 commuters' behavior during a one-week period. Marginal effect of trip-chaining stops is 0.0474 which indicates an increase of the variable from 0.5 units below the mean to 0.5 units above the mean increases the probability of using multiple routes 4.74 percent. People with greater work schedule flexibility are more likely to use multiple commute routes. Based on the model, increasing arrival time flexibility [A30more] can increase probability of using multiple routes. For example, holding all the independent variables at their mean, one unit increase of [A30more] (Number of commutes whose arrival time deviates greater than 30 minutes compared to the median arrival time) will increase the probability of using multiple commute routes by 9.74 percent. The authors speculate that this arrival time flexibility may allow commuters to more readily experiment with alternative routes, while not facing the adverse consequences of arriving late for work.

Among the primary route variables, based upon model 2, an increase of the number of idle stops will increase the probability of choosing multiple commute routes. Based on model 4, however, commute distance and the number of idle stops do not have a significant impact on commuter's decision of using multiple routes or not. This finding is consistent with Abdel-Aty et al. (14), who reported that commute distance did not seem to have a significant effect on using alternative routes. Mahmassani et al. (16) found the propensity to use multiple routes decreased with the increase of average speeds in their study. However, travel speed is not significant in our model based on the univariate model.

Among the socio-demographic variables, based on model 3, the age group dummies (one dummy variable for age group younger than 45 and one dummy variable for age group older than 52) and income dummy (1 if income>$100,000, 0 if else) have a significant impact on the dependent variable. Commuters with higher household income have higher propensity to choose multiple commute routes. Age group 45 to 52 have higher propensity to choose multiple routes compare to the other two age groups. In model 4, the dummy variable for age group less than 45 remains significant. Abdel-Aty et al. (5) also found a correlation between income and using alternative routes in their study; the fraction of individuals with alternative routes (percent of multiple route users within each income category) increases from 6.7 percent among those with incomes less than $25,000 to 28 percent among those with incomes more than $100,000 in their sample. Abdel-Aty et al. (14) found the same relationship for level of education: highly educated people tended to use alternative routes. Gender is not significant in the model presented in this paper. This finding is not consistent with previous research. Mannering and Kim (15) and Mannering (1) reported that men were more likely to change routes than women. Familiarity of network is expected to have influence on commuters' propensity of using alternative routes. Assuming tenure of residence as an indicator of familiarity of the area, researchers expect that longer tenure of residence will indicate higher propensity of using alternative routes, but since most drivers in the sample have been living in the current location for more than three years, the effect of this variable was not evident in this sample.

CONCLUSION

A large amount of research on the dynamics of route choice behavior is based on laboratory-like experiments that repeatedly ask the participants to respond to hypothetical route choices (20). In contrast to previous research, the work reported here is based on real data of drivers' choices from field observations. The empirical analysis examined the choice between using single or multiple morning commute routes. The results indicate the strong explanatory power of work schedule flexibility and trip-chaining on the dependent variable comparing to the commuters' socio-demographic characteristics and commute route related attributes.

One limitation of this model is that the impact of traffic information on travelers' pre-trip route planning and en-route diversion is unknown. The travelers' decision-making process, their perceptions and knowledge about these routes are also unknown in this study. An important area for further research is to combine the field observation with a follow-up survey about the traveler's decision making process and information utilization.

Researchers hypothesize that a model combining the impact of traffic information will have stronger explanation power. An example of this comprehensive approach can be found in the ongoing study of Doherty et al. (21), which combines GPS and GIS technologies with a recently developed computerized activity scheduling survey. This study has the potential to simultaneously observe detailed spatial-temporal activity-travel patterns and underlying decision processes of individuals within a household over long periods of time, while at the same time minimizing respondent burden.

Since commuters usually have more flexibility in aspect of departure time and route choice in evening commute comparing to morning commute. A possible expansion of the study to the evening commute route choice behavior should provide more insight on the topic.

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LIST OF TABLES AND FIGURES

Table 1 Number of Commute Routes

Number of Routes	*Number of Commuters*	*Number of Routine Routes*	*Number of Commuters*
1	73 (40.1%)	1	122 (67.0%)
2	54 (29.7%)	2	54 (29.7%)
3	35 (19.2%)	3	6 (3.3%)
4	16 (8.85)	4	0 (0.0%)
5	4 (2.2%)	5	0 (0.0%)
Total	182 (100.0%)	Total	182 (100.0%)

Table 2 Independent Variables Summary

Variable	*Definition*	*Mean*	*SD*
Commute Info			
Trip-chaining stops	Number of trip-chaining stops during the 10 days	3.97	4.55
Dless5	Number of commutes whose departure time deviate less than 5 minutes compared to the median departure time of the 10 days	4.52	2.63
A30more	Number of commutes whose arrival time deviate more than 30 minutes compared to the median arrival time of the 10 days	1.87	2.21
Primary Route Info			
Distance	Average commute distance in miles	15.90	10.84
Travel time	Average travel time (stopping time excluded) in minutes	30.84	15.67
Speed	Average travel speed in mph	29.36	10.13
Duration	Average commute duration (stopping time included) in minutes	37.40	19.63
Number of idle stops	Average number of idles (speed less than 5mph for at least 1 minutes)	2.30	1.47
Percent of freeway	Percentage of freeway travel distance compared to total travel distance	26.93%	29.93%
Number of traffic signals	Number of traffic signals	7.14	4.55
Socio-demographic (dummy variables)			
Gender	Male: reference group	49.45 %	
	Female	50.55 %	
Age group	Between 45 and 52: reference group	26.37%	
	Less than 45	46.15%	
	More than 52	27.47%	
Education	Less than college: reference group	34.62%	
	College and above	54.95%	
	Unknown	10.44%	
Household income	Income less than $100,000: reference group	54.95%	
	Income larger than $100,000	42.86%	
	Unknown	2.20%	
Residence type	Single house: reference group	89.01%	
	Apartment or townhouse	6.04%	
	Unknown	4.95%	
Tenure at residence	Less than one year: reference group	2.20%	
	One to three years	14.84%	
	More than three years	78.02%	
	Unknown	4.95%	

Table 3 Independent Variable Correlation Table

	trip-chaining stops	dless5	a30more	distance	idle stops	age group1	age group2	income
trip-chaining stops	1							
dless5	-0.2144	1						
a30more	0.1117	-0.5882	1					
distance	0.3938	-0.1612	0.0308	1				
idle stops	0.5414	-0.2252	0.0713	0.4183	1			
age group1	0.0217	-0.1419	-0.0455	0.0367	0.0761	1		
age group2	-0.0139	0.1974	-0.0635	-0.0471	-0.1039	-0.5501	1	
income	-0.0085	-0.1219	0.1450	0.0542	0.0090	-0.1461	0.1014	1

Table 4 Model Estimates

Variable	*Model 1*		*Model 2*		*Model 3*		*Model 4*	
	Coef (Odds)	*t (p)*	*Coef (Odds)*	*t (p)*	*Coef (Odds)*	*t (p)*	*Coef (Odds)*	*t (p)*
Commute Info								
Trip-chaining stops	0.2220	4.15					0.2278	3.34
	(1.2486)	(0.000)					(1.2558)	(0.001)
Dless5	-0.1516	-1.77					-0.1490	-1.62
	(0.8593)	(0.077)					(0.8815)	(0.106)
A30more	0.4441	3.15					0.4695	3.08
	(1.5590)	(0.002)					(1.5992)	(0.002)
Primary Route Info								
Distance			0.0177	1.05			0.0086	0.41
			(1.0178)	(0.293)			(1.0087)	(0.680)
Number of idle stops			0.4013	3.05			0.1135	0.68
			(1.4938)	(0.002)			(1.1202)	(0.498)
Socio-demographic								
Age less than 45					-0.7406	-1.86	-1.2730	-2.49
Age larger than 52					(0.4768)	(0.063)	(0.2800)	(0.013)
					-0.7978	-1.86	-0.6550	-1.21
					(0.4503)	(0.072)	(0.5195)	(0.226)
Household income larger than $100,000					0.6747	2.08	0.4696	1.15
					(1.9634)	(0.038)	(1.5994)	(0.252)
Model Summary Statistics								
Constant	-0.2420	0.20	-0.7302	0.028	0.7212	0.038	-0.0332	-0.04
Log Likelihood at Zero	-121.65		-121.65		-119.29		-118.35	
Log likelihood at convergence	-88.87		-113.07		-114.94		-81.42	
Prob>Chi2	0.0000		0.0000		0.0133		0.0000	
Pseudo R-square	0.2695		0.0705		0.0365		0.3120	
Number of observations	181		181		178		177	

Table 5 Changes in Predicted Probabilities

	from: x=min	to: x=max	dif: min->max	from: x=0	to: x=1	dif: 0->1	from: x-1/2	to: x+1/2	dif: x-1/2->x+1/2	from: x-1/2sd	to: x+1/2sd	dif: x-1/2sd->x+1/2sd	Marginal Effect
Trip-chaining stops	0.5071	0.9899	0.4828	0.5071	0.5637	0.0566	0.6808	0.7281	0.0473	0.5898	0.7989	0.2091	0.0474
Dless5	0.8233	0.5121	-0.3112	0.8233	0.8006	-0.0227	0.7203	0.6893	-0.031	0.744	0.6628	-0.0812	-0.031
A30more	0.497	0.9908	0.4939	0.497	0.6124	0.1154	0.6539	0.7514	0.0974	0.5873	0.8005	0.2133	0.0976
Distance	0.677	0.7661	0.0891	0.676	0.6779	0.0019	0.7041	0.7059	0.0018	0.6954	0.7144	0.019	0.0018
Number of idle stops	0.6483	0.794	0.1457	0.6483	0.6737	0.0254	0.6931	0.7167	0.0236	0.6873	0.7221	0.0347	0.0236
Age less than 25	0.8095	0.5433	-0.2662	0.8095	0.5433	-0.2662	0.8187	0.5584	-0.2603	0.7665	0.6349	-0.1316	-0.2648
Age larger than 52	0.7413	0.5981	-0.1432	0.7413	0.5981	-0.1432	0.7683	0.6327	-0.1356	0.7346	0.6735	-0.0611	-0.1362
Household income higher than $100,000	0.6602	0.7566	0.0963	0.6602	0.7566	0.0963	0.6539	0.7514	0.0975	0.6801	0.7287	0.0486	0.0977

Figure 1 Outside Look of the EDR

Figure 2 EDR and Accessories

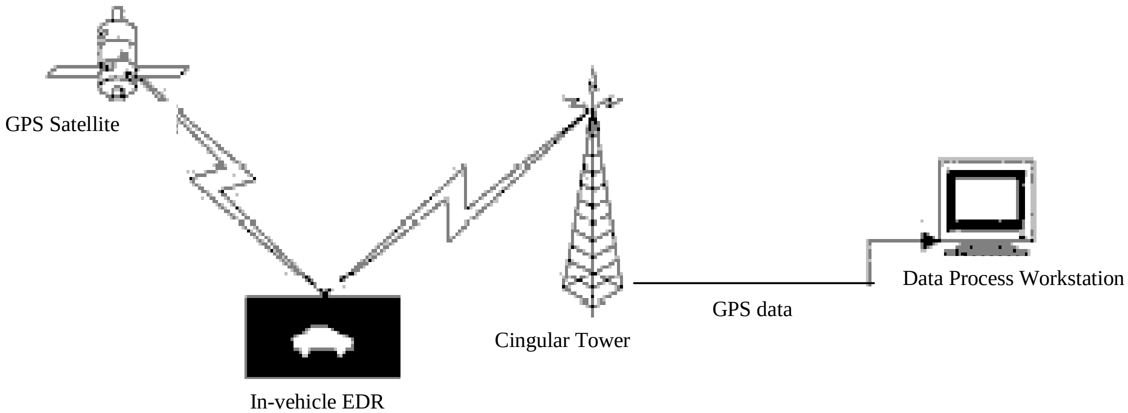

Figure 3 Commute Atlanta Data Collection System Map

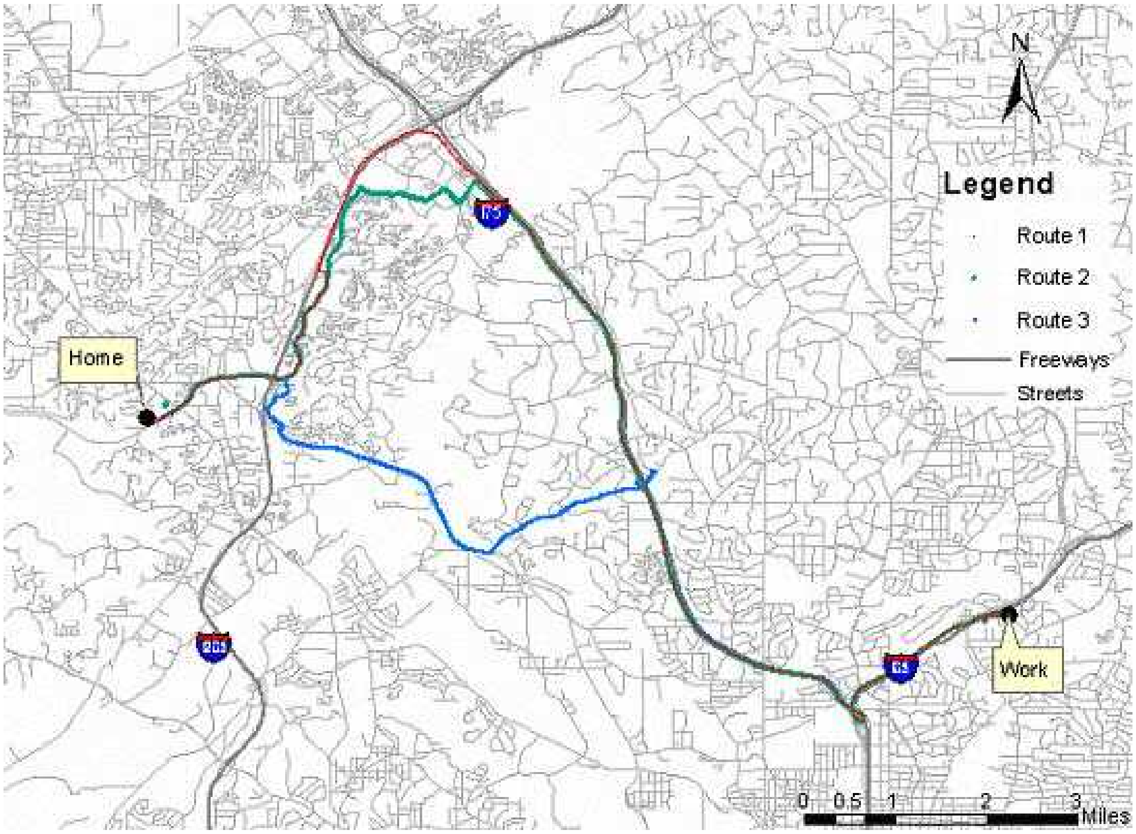

Figure 4 An Example of Commute Route Choice