Investigating Effect of Travel Time Variability on Route Choice Using Repeated-Measurement Stated Preference Data

MOHAMED A. ABDEL-ATY, RYUICHI KITAMURA, AND PAUL P. JOVANIS

A study was conducted to determine ways in which travel time variation affects route choice behavior and the potential interplay among travel time variation, traffic information acquisition, and route choice. In a computer-aided telephone interview, a stated preference section was included to investigate this issue, and 564 respondents in the Los Angeles area gave their choices to five hypothetical binary choice sets. The repeated measurement issue is addressed with individual-specific random error components in a binary logit model with normal mixing distribution. The results indicate the significance of both the degree of travel time variation and traffic information on route choice and illustrate the viability of the survey methodology used. The study also underscores the need for a statistical correction to account for the correlation among error components in repeated-measurement data.

In recent years, with an increased desire for better urban transportation systems arising from environmental and increased levels of traffic congestion concerns, there has been an increased need for better modeling in the transportation planning process. Much of the emphasis has been on gaining a better understanding of an individual's route choice behavior. It is in the area of traffic assignment that a better understanding of that behavior would be beneficial.

TRAVEL TIME UNCERTAINTY AS CONTRIBUTING FACTOR TO ROUTE CHOICE

Several empirical studies have examined the factors affecting drivers' route choice. In the urban context the governing relationship is not clear; some researchers have concluded that time minimization is the dominant criterion, whereas others have noted the importance of other factors, such as road type (*1,2*); avoidance of congestion (*1*); and avoidance of stops and traffic signals (*3*).

The reliability of a particular route can be expected to play an important role in the traveler's route choice behavior. In several attitudinal studies, reliability-related attributes have been found among the most important service attributes in a variety of situations (*4*). Black and Towriss (*5*) indicated that travelers are likely to suffer disutility because of the uncertainty or unreliability in travel times. However, the effect of travel time variation has been rarely investigated in route choice studies. In an empirical study by the authors (*6*), travel time reliability was found as one of the most important factors for route choice, with about 54 percent of respondents in a route choice survey indicating that travel time reliability is either the most important or second most important reason for choosing their primary commute routes.

The Wardrop user equilibrium model states that travelers choose the fastest available route; it implies that they always choose the same route on repeated trips (*7*). However, travelers are not always capable of identifying the fastest route, and if travel time is uncertain, they may wish to acquire additional information that helps to select a better route. Therefore, investigating the effect of travel time reliability is significant in understanding the impact of traffic information on route choice.

Several studies by the authors have investigated the effect of numerous criteria on route choice behavior (*8–10*). The main objective of this study is to explore one measure of reliability—travel time variability—and assess its importance on route choice. The possible interplay between traffic information, travel time variability, and route choice will also be addressed. Five stated preference choice sets were included in a route choice survey to investigate the effect of travel time variation on route choice. This repeated measurement data set is used in the modeling effort presented in this paper.

REVIEW OF DISCRETE CHOICE MODELS WITH REPEATED-MEASUREMENT DATA

Discrete choice models typically are estimated on the basis of revealed preferences, with a single choice made by each respondent in the sample. Under these conditions, the disturbance term (ε) accounts for the taste variation from one decision maker to another. In contrast to the revealed preference approach, repeated hypothetical choice sets are often presented to the decision makers in the stated preference approach.

The estimation of a discrete choice model with repeated observations for each respondent gives rise to an obvious correlation of disturbances, or heterogeneity, which refers to variations in unobserved contributing factors across behavioral units. If behavioral differences are largely caused by unobserved factors, and if unobserved factors are correlated with the measured explanatory variables, then estimates of model coefficients will be biased if this heterogeneity is not taken into account. The problem may be more pronounced in repeated measurement data because such unobserved factors may be invariant across the repeated measurements. In this paper, an error component method is used to account for unobserved heterogeneity and correct for potential bias that would otherwise arise.

Many studies, for example, Bunch et al. (*11*), ignored the effect of heterogeneity by indicating that in a small number of repeated observations by each individual the properties of parameter estimates themselves do not rely on the strict independence assump-

M. A. Abdel-Aty, Department of Civil and Environmental Engineering, University of Central Florida, P.O Box 162450, Orlando, Fla. 32816. R. Kitamura and P. P. Jovanis, Institute of Transportation Studies, 2028 Academic Surge, University of California at Davis, Davis, Calif. 95616.

tion, and the benefits of using a much larger pooled data set more than outweigh this concern.

Mannering and Winston (*12*) presented a dynamic model composed of nested-logit models of car ownership level and vehicle type choice, combined with linear utilization models. The paper emphasizes dynamic aspects of car ownership and utilization behavior, for example, stationarity and state dependence. However, it neglects completely the possible intertemporal correlation in the error terms. Mannering (*13*) discusses the same model system but assumes that disturbances are serially independent because of the difficulty in accounting for serial correlation in the presence of lagged endogenous variables in discrete choice models. Hocherman et al. (*14*) estimated a nested logit dynamic household vehicle transaction model assuming that serial correlation is not present.

Louviere and Woodworth (*15*) corrected the standard errors produced by a repeated responses regression model by multiplying the standard errors by the square root of the number of repeated observations. Mannering (*16*) estimated a vehicle choice logit model with repeated observations and also used the same correction procedure. However, this method is said to be a conservative approach and tends to overcorrect the value of the standard errors (*15*) (or *t*-statistics when divided by the square root of the number of observations for each respondent).

A number of other discrete choice panel data models have been discussed in the literature, usually limited to the dichotomous case. One of the oldest models is the beta-logistic model proposed by Heckman and Willis (*17*). In this model heterogeneity is introduced by specifying the beta distribution as a mixing distribution on the outcomes. The exogenous variables are assumed to be time invariant. The presence of heterogeneity in mode choice models is shown in Uncles (*18*) also using a beta-logistic model.

Kitamura and Bunch (*19*) used a dynamic ordered-response probit model with error components of car ownership. This approach allows more flexible formulation of the error terms and thus offers a better accounting of heterogeneity than do the beta-logistic models suggested by Heckman and Willis (*17*) and Uncles (*18*). Morikawa (*20*) also used logit models with error components to treat serial correlation (heterogeneity) between the error terms of revealed and stated preference models.

Incorporating the effect of the correlation of disturbances into repeated observations, discrete choice models must be addressed explicitly if unbiased estimates of the structural parameters are to be obtained. This paper is concerned primarily with the empirical results investigating the effect of travel time variation on route choice. However, heterogeneity will be accounted for by using a parametric functional form (normal mixing distribution and Gaussian quadratures estimation). Comparative analysis will be performed using the pooled data and applying the heuristic correction procedure suggested in other studies (*15,16*) and using one observation randomly drawn from each respondent. A subsequent paper will concentrate on different specifications of the error components, that is, parametric estimation with different distributions and nonparametric estimation.

ROUTE CHOICE SURVEY

An ongoing effort for the Partners for Advanced Transit and Highways at University of California, Davis, is to investigate the actual route choices of drivers, with the objective of developing refined route choice models that can include the effect of traveler information.

To probe into drivers' route choice behavior, a computer-aided telephone interview (CATI) of Los Angeles-area morning commuters was conducted. The survey, undertaken in May and June 1992, was designed to investigate how much information drivers have about their routes; their awareness of alternate routes; their awareness of traffic conditions, which could affect their route choices; and their use of available traffic information either en route or pretrip, or both. A detailed description of the survey design and descriptive statistics are included in a research report by the authors (*8*), and models of information use and route choice and of commuters' frequency in changing routes are reported in Abdel-Aty et al. (*9*).

A second CATI survey was designed and conducted in May 1993. Its objectives were to probe further into drivers' route choice behavior, to measure any changes within the last year, to investigate commuters' attitudes and perceptions about several commute characteristics, and to understand the effect of travel time variation on route choice. The survey targeted the same sample interviewed in May and June 1992. A maximum of 10 callbacks were attempted before abandoning a respondent's number, which yielded 564 (about a 60 percent response rate) completed interviews (1 year after the first survey of May and early June 1992). Abdel-Aty et al. (*21*) describe the survey design, and introduce general descriptive statistics that show commuters' perceptions, preferences, and decisions in route choice. Factor analysis was performed to investigate the commuters' perceptions of several commute route characteristics.

This paper is concerned with the last objective of the survey, which is to measure and investigate whether commuters choose a route that is longer but more reliable or a route that is shorter but has uncertain travel times and to what extent uncertainty affects route choice. The paper presents models of the effect of travel time variation on route choice and the possible interplay between travel time variation, traffic information, and route choice.

DESCRIPTION OF HYPOTHETICAL CHOICE SETS

The advantage of using revealed preference (RP) data is that resulting models are based on the observation of actual behavior, not on respondents' responses to questions about their intentions. However, the family of market research survey techniques, termed stated preference (SP) methods, has been used often in transportation planning over the past decade [e.g., Morikawa (*20*) and Khattak et al. (*22*)]. Such methods are now becoming seen as a complement to the more traditional RP survey methods in cases where the latter cannot provide the full information needed for analysis. Investigating the effect of travel time variation on commuters' route choice would be difficult largely because it is time consuming to collect data that support the analysis. Therefore, in the context of this study there is no alternative but to solicit preferences in hypothetical settings, as is often done in many marketing research contexts.

It was therefore decided to include repeated hypothetical choice sets in the CATI survey. A major concern was that the design of SP choices could be complicated because the intention was to quantify the tradeoffs between a reliable but slow route versus an unreliable but fast route. It was intended also to make the design of the choice sets as easy as possible to be understood on the telephone, which was the medium chosen for the survey (in mail questionnaires more complete and complicated SP choice scenarios can be formulated, whereas in telephone interviews there is a limitation to what a

respondent can comprehend and visualize). Another concern was that the degree of travel time variation needed to be as realistic as possible. The SP choices were thus designed to be as simple as possible so that respondents can comprehend and present their choices on the telephone.

Five SP choices are included in the survey. In each choice the respondent is asked to choose between two hypothetical routes. The first route has a fixed travel time every day (5 days a week), whereas the second route has the possibility that the travel time increases on some day (s). For example, Route 1 has a travel time of 30 min every day, whereas Route 2 takes 20 min 4 days per week and 40 min 1 day per week. In this case respondents are informed that if they choose Route 1, they are certain that travel time will be 30 min every day, but if they choose Route 2 they must expect that it is possible that on any one day of the week travel time could be 40 min and on the other 4 days it could be 20 min.

The choices are designed such that the travel time on the first route is always longer and certain, whereas that of the second route is shorter but uncertain. The mean travel time on the second route changes and reaches in some choices the mean of Route 1. The sequence of the choices is randomized across respondents to avoid any ordering biases.

Table 1 presents the five stated preference questions, and the mean and standard deviation of travel times and observed frequency of choices for each case (only Columns 2 and 3 were presented to the respondent in the interview). The average travel time on Route 2 ranged between 24 and 30 min, whereas the mean travel time on Route 1 was 30 min. The standard deviation ranged between about 5 min (Case 3) and about 33 min (Case 5).

Turning to the frequency of choices for each case, it is clear that (*a*) in Cases 2, 4, and 5 the majority of the respondents had chosen Route 1; (*b*) these cases have the largest standard deviations on Route 2 (>10 min); and (*c*) the mean travel time on Route 2 is either 28 or 30 min. In Case 1 both routes were almost equally chosen, the mean and standard deviation on Route 2 are 24 and about 9 min, respectively. In Case 3, where the standard deviation is the least and the mean is 24 min, Route 2 was chosen by the majority of the respondents.

Figure 1 depicts the relationship between the standard deviation of travel times on Route 2 and the frequency of each alternative being chosen. Figure 1 and Table 1 illustrate that the respondents correctly recognize the time savings and degree of variation and are willing to tolerate travel time variation to a certain limit, after which they are more likely to use the certain (although slightly longer) route.

ROUTE CHOICE MODELING

In this section, two sets of models are estimated. The first uses the pooled data set that contains all repeated choices, and the second is based on a randomly drawn observation for each respondent.

Route Choice Models Using Repeated Observations

In developing statistical models of repeated discrete choice, a central concern is the identification of the structural parameters of exogenous determinants of choice behavior, while controlling for other influences on behavior. These other influences include such effects as state dependence, initial conditions, nonstationarity, and omitted variables and unobservable variables such as taste and motivation. In the context of the data from the short-term repeated-choice sets analyzed in this paper, it is possible to argue that the values of most exogenous determinants of choice behavior remain constant over time and that the assumptions of stationarity and the lack of state dependence are reasonable. The lack of state depen-

TABLE 1 Stated Preference Choices

Case	Route	Route Description	Travel Time: Mean (min/day)	Travel Time: Standard Deviation (min)	Delay per Day (min)	Expected Travel Time Saving of Route 2 per week (min)	Stated Choices
1	1	30 min every day	30	0	0	—	310
	2	20 min 4 days/week 40 min 1 day/week	24	8.94	4	30	254
2	1	30 min every day	30	0	0	—	476
	2	20 min 4 days/week 60 min 1 day/week	28	17.89	8	10	88
3	1	30 min every day	30	0	0	—	159
	2	20 min 3 days/week 30 min 2 days/week	24	5.48	4	30	405
4	1	30 min every day	30	0	0	—	454
	2	20 min 3 days/week 45 min 2 days/week	30	13.69	10	0	110
5	1	30 min every day	30	0	0	—	496
	2	20 min every day 120 min 1 day/2 week	30	33.54	10	0	68

NOTE: delay/day = mean − usual travel time (most frequent) expected saving in travel time of Route 2 = travel time on Route 1/week-travel time on Route 2/week = difference in expected travel time between Routes 1 and 2/week

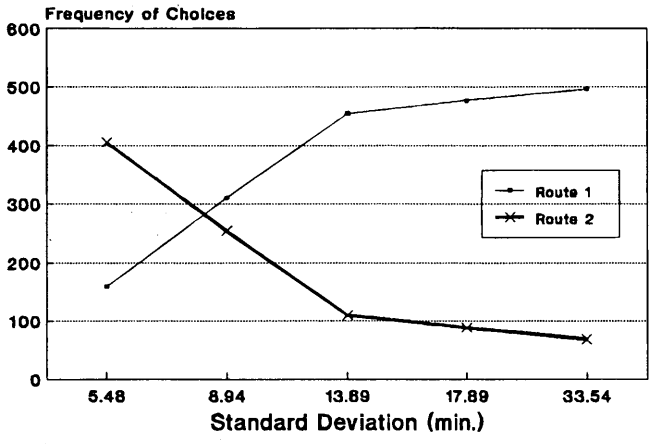

FIGURE 1 Relationship between frequency of observed choices and standard deviation.

dence in its turn implies exclusion of initial conditions (*23*). Empirical evidence for the assumption of a lack of state dependence in this context is available in the work of Uncles (*24*).

Given the simplifying assumptions of stationarity and lack of state dependence, one is left with the problem of controlling for omitted and unobserved variables whose influences are defined collectively as unobserved heterogeneity. If the possible existence of unobserved heterogeneity is not recognized and accounted for in the model's econometric structure, the model will have biased coefficients. Also, because the pooled data set includes repeated observations from each individual, the strict independence among choices and the asymptotic standard errors would be understated.

Methodological Approach

The approach taken in this paper to account for unobserved heterogeneity is to assume a parametric functional form for the pattern of the heterogeneity. The vector of observed choices or responses for individual i is defined as y_i. Each element of y_i is written as y_{it}:$t = 1, \ldots, T_i$, each of which is a repeated binary choice, expressed as the integers 0 and 1. The length of y_i is T_i, which may vary between individuals. The sample size is written as I, so $i = 1, \ldots, I$.

The assumptions of lack of state dependence, stationarity, constant exogenous variables, and constant probabilities over the repeated choices facilitate the writing of the probabilities that individual i chooses alternatives 0 or 1, P_{0it} and P_{1it}, respectively, in the standard logistic regression form

$$p_{0it} = P(y_{it} = 0 | \alpha, \beta, x_{it}) = 1 / [1 + \exp(x_{it}'\beta + \alpha)]$$

$$p_{1it} = P(y_{it} = 1 | \alpha, \beta, x_{it}) = \exp(x_{it}'\beta + \alpha)/[1 + \exp(x_{it}'\beta + \alpha)] \quad (1)$$

where

α = constant;
β = vector of parameters, and
x_{it} = vector of exogenous variables.

The influence of the unobserved variables in Equation 1 is represented by the constant term α; that is, the influence is assumed constant across individuals. The probability of observing y_i given T_i in this specification is

$$P(y_{it} | \alpha, \beta, T_i, x_{it}) = \prod_{t=1}^{T_i} \left[\frac{\exp(x_{it}'\beta + \alpha)}{1 + \exp(x_{it}'\beta + \alpha)} \right]^{D_{1i}} \quad (2)$$

$$D_{it} = \begin{cases} 1 & \text{if } Y_{it} = 1 \\ 0 & \text{otherwise} \end{cases}$$

Heterogeneity is introduced into the model by assuming that the probabilities p_{0it} and p_{1it} are conditional on both x_{it} and an individual specific error term, ξ_i, which represents all the other influences. Equation 1 becomes

$$p_{0it} = P(y_{it} = 0 | \beta, x_{it}, \xi_i) = 1/[1 + \exp(x_{it}'\beta + \alpha + \xi_i)]$$

$$p_{1it} = P(y_{it} = 1 | \beta, x_{it}, \xi_i) = \exp(x_{it}'\beta + \alpha + \xi_i)/[1 + \exp(x_{it}'\beta + \alpha + \xi_i)] \quad (3)$$

The ξ_i: $i = 1, \ldots, I$ are assumed to be identically distributed with density function $f(\xi)$ independent of the x_i, so that Equation 2 becomes

$$P[y_{it} | \beta, T_i, x_{it}, f(\xi_i)] = \int_{-\infty}^{+\infty} \prod_{t=1}^{T_i} \left[\frac{\exp(x_{it}'\beta + \alpha + \xi_i)}{1 + \exp(x_{it}'\beta + \alpha + \xi_i)} \right]^{D_{it}} f(\xi_i)\, d(\xi_i) \quad (4)$$

This yields a marginal likelihood function. The unknown variables ξ are integrated out. Equation 4 is based on the assumption that ξ has a continuous distribution function. The distribution of ξ_i is called a mixing distribution. The log likelihood function is

$$L = \sum_{i=1}^{I} \ln \int_{-\infty}^{+\infty} \prod_{t=1}^{T_i} \left[\frac{\exp(x_{it}'\beta + \alpha + \xi_i)}{1 + \exp(x_{it}'\beta + \alpha + \xi_i)} \right]^{D_{it}} f(\xi_i)\, d(\xi_i) \quad (5)$$

A parametric form and $\xi_i \sim N(0, \sigma^2)$ are assumed. The integral is evaluated using Gaussian quadratures. General MLE packages, such as the one provided with GAUSS statistical software (*25*) can be used for this problem. The Broyden, Fletcher, Goldfarb, and Shanno (BFGS) optimization method is used (*26*). The BFGS method is similar to the Newton method in that it uses both first and second derivative information . However, in BFGS the Hessian is approximated, reducing considerably the computational requirements, and although it takes more iterations than Newton it converges in less overall time.

Estimation Results

A binary logit model is developed using the methodology presented above. The model is developed to estimate the commuters' choice between Route 1 (longer with reliable travel time) and Route 2 (shorter with uncertain travel time). The overall observations are used to estimate the models, which give a total of 2,820 observations (i.e., 564 respondents, each making five choices). The data used for estimating the model came from the two CATI surveys (e.g., perception of shorter distance) and Table 1 (e.g., standard deviation of the travel time).

The model is presented in the first part of Table 2 and shows that commuters' perceptions and attitudes have important effects on their choice; that is, if respondents perceive shorter travel distances as being extremely or very important, then they are likely to choose Route 2 in trying to minimize their travel time.

The standard deviation of the travel time on Route 2 has a negative coefficient, indicating that the more the variation in travel time on Route 2, the less likely this route is to be chosen. This result shows that commuters realize travel time and its variability on alternative routes and try to minimize them. Also, the larger the difference in the expected travel time between Routes 1 and 2, the more likely the respondent chooses Route 2, indicating that commuters realize the savings in travel time and choose the route that achieves a minimum travel time. These two variables show clearly that commuters try to minimize their travel time but only if travel time variation is acceptable. If travel time varies significantly on a particular route then commuters will choose the longer certain route.

Receiving traffic information is a very significant variable in this model. Information is more likely to affect the degree of uncertainty and hence influences the commuter's route choice. Acquiring traffic information could be treated as either an endogenous or an exogenous variable. Commuters receive information because of personal reasons (e.g., to reduce their degree of uncertainty) or because of their commute characteristics (e.g., long commute trip). Therefore receiving pretrip traffic information is most likely to be an endogenous variable; thus the variable was instrumented using a binary logit model estimated in Abdel-Aty et al. (*8*)—the data used in the instrument come from the first CATI survey, i.e., commute distance, gender, traffic conditions on the regular commute route, and perception of the uncertainty of travel time. The variable has a significant positive coefficient that indicates that commuters who listen to pretrip information are more likely to choose the uncertain route, possibly because they are confident that they can know if there is a delay on a particular day and avoid this route. The significance of the information variable validates the SP choice sets used in this study because people do acquire information in the real world to reduce their uncertainty.

Gender also had a significant effect on route choice. Males are found to be more likely to choose Route 2. This indicates that males are more risk prone and are ready to choose uncertain routes in trying to minimize their travel time.

Finally, the significance of σ illustrates that the unobserved influences affecting a specific individual's choice are correlated from one of his or her selections to the next.

A second model that describes the route choice with normal mixing distribution was estimated. This model is similar to the model presented in Table 2, but receiving pretrip traffic information is substituted by receiving en route information. This model is similar to a large extent to that shown in Table 2. However the overall fit of the first model (including the effect of pretrip information) is slightly better (log likelihood of $= -1133.804$ versus -1135.078). Also the *t*-statistics of receiving pretrip information are significant at the 95 percent level of significance, whereas receiving en route information was significant only at the 90 percent confidence level. As found in a previous study (*10*), commuters might value and use pretrip information more than en route information because it notifies them of the status of their routes in advance, which enables them to change route or departure time, or both. In the context of this study, traffic information, particularly pretrip, will help reduce the degree of uncertainty when commuters encounter a variation in travel time on their routes.

The inclusion of both types of information in a model was attempted, but this caused problems in the model estimation because of multicollinearity. A possible extension of this work is to estimate a similar model that considers whether the respondent receives pretrip or en route traffic information.

TABLE 2 Estimates Describing Route Choice with Normal Mixing Distribution and Gaussian Quadrature Estimation Using Pooled Data and Randomly Drawn Observation, Including Effect of Pretrip Traffic Information

	Normal mixing distribution		Pooled repeated measurement			Randomly drawn observation	
	Coef.	t-stat.	Coef.	t-stat.	correc. t-stat.	Coef.	t-stat.
Constant	-2.394	-5.89	-1.655	-6.45	-2.88	-1.199	-2.08
X_1 Attitude toward shorter distance dummy (1 if extremely or very important, 0 otherwise)	0.550	3.26	0.391	4.22	1.89	0.212	1.06
X_2 Standard deviation of travel time on Route 2 (min.)	-0.067	-6.32	-0.052	-5.67	-2.54	-0.065	-2.99
X_3 Difference in expected travel time between Route 1 & 2 /week	0.067	10.31	0.048	8.99	4.02	0.031	2.61
X_4 Receive pre-trip information - instrumented	0.416	2.54	0.294	3.84	1.72	0.276	1.71
X_5 Male dummy variable	0.548	3.25	0.372	4.08	1.82	0.432	2.18
σ Standard Deviation of ξ_i	1.462	13.51					
Summary Statistics							
Log Likelihood at zero	-1954.675		-1954.65			-390.93	
Log Likelihood at market share	-1784.392		-1784.39			-351.66	
Log Likelihood at convergence	-1133.804		-1477.12			-307.86	
Likelihood ratio index	0.419		0.244			0.213	
Number of observations = 2820 (564 respondents)	2820		2820			564	

Models Using Pooled and Randomly Drawn Data

The same model presented earlier is estimated using the same model specifications such as (*a*) pooled repeated measurement data and correcting the *t*-statistic by dividing it by the square root of the number of observations for each respondent [this heuristic method was used in Louviere and Woodworth (*15*) and Mannering (*16*)] and (*b*) one observation randomly drawn from each respondent. The models are also presented in Table 2 to facilitate comparisons among the three models.

A comparison of the three models presented in Table 2 indicates that the results of the pooled data model, after correcting the *t*-statistics value, and the randomly drawn observation model are to a great extent close. The *t*-statistics of the model estimated using the mixing distribution and that of the uncorrected pooled data model are comparable to a large extent (mixing distribution produced the largest *t*-statistics for route-specific attributes, whereas pooled data tended to give the highest *t*-statistics for individual attributes). It is apparent that the corrected pooled data model produces a conservative estimate of the *t*-statistic values, which might have overcorrected these values. On the other hand, the model with the randomly drawn observation lacks the benefits of using additional information in the much larger pooled data set. Figure 2 compares the coefficient estimates of the three models and shows that the coefficients are similar for some of the variables, that is, standard deviation and difference in expected travel time (route-specific attributes). On the other hand, the coefficients are different for other variables.

These comparisons illustrate the need for a method to account for heterogeneity. The use of normal mixing distribution is used in this paper. However, extending this effort to include different mixing distributions and nonparametric distributions remains as a future task.

CONCLUSIONS

The primary conclusion of this research is that a specific measure of travel time reliability, variability of travel time, has an important impact on the route choice behavior. It is clear that the choice sets could not be posed to the respondents in formal statistical terms, such as mean and standard deviation. However, the results showed that using repeated hypothetical choice sets while varying travel time on one of the routes is a viable method. This method achieved travel time dimensions that are easily convertible to the more formal statistical measures, which are desirable from the modeler's standpoint. More impressively, the respondents understood the degree of variation and responded rationally.

The results of the models estimated using the stated preference route choices yielded important insights into the commuters' route choice in general and the tradeoffs involved in the choice between a route that is longer but has reliable travel time versus another route that is shorter but has an uncertain travel time. The models that are estimated either by using single or repeated observations for each respondent show that both expected travel time and variation in travel time influence route choice; commuters' attitudes toward several commute characteristics (e.g., distance and traffic safety) influence route choice; and, among the socioeconomic factors, gender has a significant effect on route choice.

Receiving traffic information is found to have a significant effect in the models. Information might be used by the commuters to reduce the degree of travel time uncertainty and enables them to choose routes adaptively.

The data also suggest that the impact of travel time variability varies substantially across individuals, ranging from those who will choose routes that are significantly longer to avoid the possibility of delay to those who are essentially expected value decision makers with respect to commute alternatives. A possible extension to this work is to introduce the idea of risk aversion and being risk prone in the route choice models and measure the bound of risk aversion.

The error components account for unobserved heterogeneity and correct for potential bias that would otherwise arise from the use of repeated measurement data. The repeated measurement issue is addressed in this study with individual-specific random error components in a series of binary logit models with normal mixing distribution. The significance of the standard deviation of the error components shows clearly the need for some formal statistical

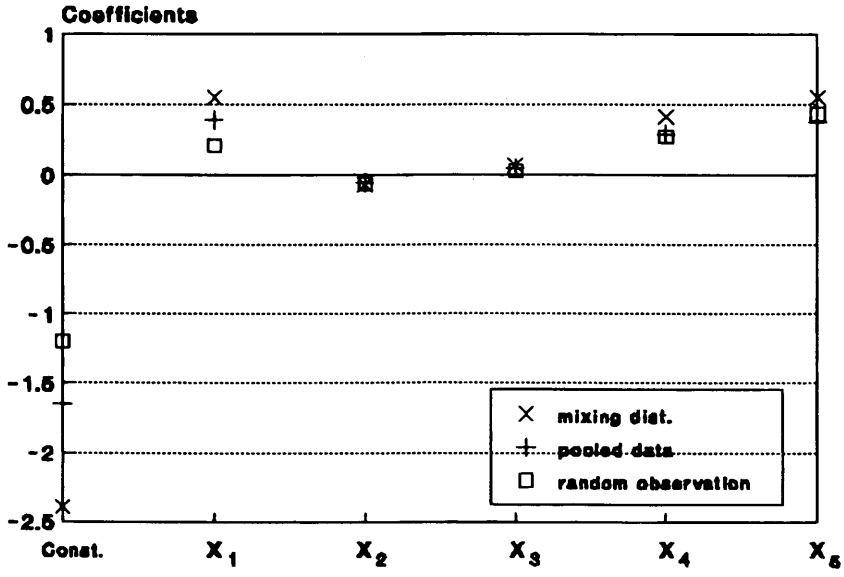

FIGURE 2 Comparison coefficient estimates of three models.

correction to account for heterogeneity. A methodological future direction is to attempt models with the same specifications using the nonparametric approach and compare them with the models presented in this paper to reach conclusions about the best way to account for heterogeneity in route choice models.

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