Heterogeneous Decision Rule Model of Mode Choice Incorporating Utility Maximization and Disutility Minimization

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With the advent of more flexible discrete choice models, the analysis of heterogeneity at the observed and unobserved levels is receiving increasing attention. However, heterogeneity in decision rules has hardly been investigated in the mode choice context. This study proposes a heterogeneous decision rule model of mode choice incorporating utility maximization and disutility minimization using empirical data from Chennai City, India. The two decision rules may yield different estimates of mode choice probabilities if the error structure is not symmetric. Therefore, a heterogeneous decision rule model is estimated by postulating separate choice behaviors for each decision segment. Because the decision rule remains latent, individuals are probabilistically assigned to the two segments. The membership propensity of belonging to each class is modeled by using a binary logit form. The performance of the proposed heterogeneous decision rule (HDR) model is compared with the pure utility maximization, pure disutility minimization, and heterogeneous latent class models. The results reveal that the HDR model outperforms these alternative specifications. Further, significant differences are observed across the decision segments for aggregate modal shares, intrinsic preference for different modes, sensitivity to modal attributes, role of subjective factors, and the effect of activity patterns and accessibility. Factors influencing the decision-segment membership propensity are also identified. These findings have important behavioral and practical implications for analysis and evaluation of travel demand management measures aimed at sustainable urban transportation systems, congestion mitigation, and transit improvement.

The important role of mode choice in travel demand modeling is well recognized given its applications related to congestion, air quality, and energy consumption. The role of heterogeneity in mode choice and several other dimensions has been well acknowledged. The main sources of heterogeneity in the existing literature include socio-demographic segmentation, choice set variability, and random taste variation. Heterogeneity in decision rules has hardly been investigated in the mode choice context to the best of the authors' knowledge. This study aims to bridge this gap by using work-trip mode choice data from Chennai City, India.

The motivations underlying this study are fourfold: First, most studies assume that all users apply the same decision rule, namely, utility maximization. Some recent studies have shown that utility maximization and disutility minimization principles may yield significantly different coefficients in discrete choice models (*1, 2*). Contrary to expectations, the probability of choosing an alternative may differ between utility maximization and disutility minimization in the random utility case when error structure is not symmetric (as discussed in the section describing the literature review). In that context, it is of interest to examine whether disutility minimization may be more appropriate for some segments in Chennai City. Developing countries such as India have certain distinct features including lower per capita income and vehicle availability, significant use of two-wheelers and availability of intermediate public transport (IPT) modes, mixed land use, overcrowding, and unreliability in public transport in which disutility minimization may be more relevant in mode choice.

Second, a heterogeneous decision rule model can offer richer insights into the behavioral characteristics of different segments. Third, the implications of homogeneous versus heterogeneous decision rule models on the sensitivity to modal characteristics remain to be explored. Finally, ignoring heterogeneity in decision rules can lead to inaccurate models and biased forecasts for planning applications noted above. In contrast, capturing heterogeneity in decision rules can facilitate the identification of suitable and effective policies for different segments.

Four objectives are pursued in this paper:

- To propose a heterogeneous decision rule model of mode choice consisting of two decision rules: utility maximization and disutility minimization behavior,
- To compare the performance of the homogeneous versus the proposed heterogeneous decision rules model,
- To investigate key factors and differences between the utility maximizing (UM) and the disutility minimizing (DM) segment, and
- To identify the major factors that influence the propensity to choose utility maximizing versus disutility minimizing decision rules.

Toward achieving these objectives, the presence of two distinct decision rule segments, namely, utility maximization and disutility minimization rules, with separate choice behaviors is hypothesized. Respondents are then probabilistically assigned to the two decision segments. The coefficients of segment membership propensity and utility and disutility specifications are estimated using the maximum likelihood technique. The performance of the proposed heterogeneous model is compared against specifications with homogeneous decision rules.

This study contributes to the study of heterogeneity in mode choice in the following respects. A heterogeneous decision rule model is proposed based on both utility maximization and disutility minimization

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principles. The empirical results are consistent with the simultaneous presence of utility maximization and disutility minimization behaviors. Differences in mode choice behavior between utility maximization and disutility minimization segments are analyzed, and salient factors that influence the selection of the two decision rules are investigated.

This paper is organized as follows. The next section presents a review of the related literature on mode choice and heterogeneity. The empirical context of the study and the data description are discussed next. In the following section the model structure of the proposed heterogeneous decision rule (HDR) model and results of baseline homogeneous and heterogeneous decision rule models are presented. The salient findings from the detailed HDR model and results from policy analysis application are presented next. The final section presents a summary of the work along with pointers for future work.

LITERATURE REVIEW

Mode choice models play an important role in urban travel demand analysis and have been extensively investigated by several researchers. Mode choice is influenced by various factors including the level-of-service attributes (e.g., travel time, fare), land use and accessibility, as well as individual and household characteristics (*3, 4*). The issue of choice set and variability across respondents has also received considerable attention (*5*).

The importance of observed and unobserved heterogeneity (variation in responsiveness to say travel time and cost, across users) in mode choice has also been recognized in the literature (*6, 7*). Observed heterogeneity is modeled largely through exogenous segmentation (e.g., vehicle ownership, income) or by specifying the coefficients as a function of other variables.

Some researchers have modeled observed heterogeneity through the use of subjective factors. For example, Algers et al. examined the role of comfort and convenience in mode choice through proxy variables such as seat availability and number of transfers (*8*). Koppelman and Lyon proposed a latent variable approach based on factor scores to measure subjective and attitudinal variables and found them to be significant in mode choice (*9*). More recently, Johansson et al., on the basis of Finnish mode choice data, reported that subjective ratings of comfort and flexibility are significant determinants of choice between bus, car, and train, but reliability and safety were not significant (*10*).

With flexible discrete choice models such as mixed multinomial logit (MMNL), attempts to capture unobserved heterogeneity have grown during the past decade. The following types of unobserved heterogeneity in mode choice have been reported:

- Random coefficients across individuals (*6, 11*),
- Variability in variance–covariance structure (*12*),
- Heterogeneity in choice set [e.g., Cascetta and Papola (*13*) and Zhang et al. (*14*)], and
- Latent variable and latent class models (*15–18*).

More recently, Fosgerau and Bierlaire proposed seminonparametric methods for capturing unobserved heterogeneity that capture features such as mass points and multiple modes in the distribution of response coefficients (*19*). Several of these studies highlight the danger of disregarding unobserved heterogeneity when present. Pinjari and Bhat caution that the misspecification of the systematic utility can be wrongly interpreted as unobserved heterogeneity (*20*).

Latent class models offer one way to capture unobserved and observed taste variation. These models assign different coefficient values to different behaviorally similar segments of the population (*21*). Because the segments are unobserved, they are classified as latent or endogenous. Latent class approaches cluster respondents into a number of market segments with similar choice behavior and develop a separate mode choice model for each cluster. In addition, the probability that an individual belongs to a segment is also determined.

Along that line, Greene and Hensher proposed a latent class–based extension of the mixed logit model for the analysis of road type chosen for long-distance travel and found that the latent class model outperforms the mixed logit model (*17*). Bhat applied an endogenous segmentation model using the expectation-maximization algorithm for intercity mode choice and showed that the latent class model outperforms alternative specifications (*21*). Recently Ben-Akiva et al. proposed a hybrid discrete choice framework that combines latent variable and latent class modeling that can allow different decision protocols, choice set formations, and unobserved market segmentation (*15*).

Compared with the random taste variation approaches, only a few studies have used the latent class approach. The advantage of the latent class models is that they enable a better characterization of taste heterogeneity on the basis of sociodemographic information than continuous mixed logit models. Latent class models may be computationally more difficult than standard discrete choice models because of the nonconcavity of the likelihood function. Further, the issues of misspecification and identification assume significance. The segments found in the latent class models may often be based solely on goodness-of-fit measures, but not necessarily with direct behavioral underpinnings in the specification. One assumption in current latent class model implementations is that all segments are assumed to follow the same decision rule but with distinct parameters.

In regard to decision rules, most mode choice studies have relied on the random utility maximization theory, given its versatility and flexibility. The random utility maximization theory assumes that users are rational and choices are consistent and transitive. Misra in a recent paper applied the random disutility minimization theory and estimated the reverse multinomial logit-based choices (*2*). With data from a marketing context, the authors establish that utility maximization and disutility minimization are distinct and can yield different coefficients. The equivalence between utility maximization and disutility minimization holds only when the error terms are symmetric. Disutility minimization models have not received adequate attention in the travel demand literature so far. Similarly, the use of other decision rules, such as the conjunctive, disjunctive, and satisfying rules, is also sparse, more so in the mode choice context. However, a few applications have been reported in destination choice (*22*), housing location (*23*), and route choice contexts (*24*).

To sum up the literature, heterogeneity has received a great deal of research attention recently and has been represented through random taste variation, variability in choice set, and differences in variance–covariance structure. Unlike these approaches that capture heterogeneity in specific variables, successful attempts have also been reported to classify choice into distinct but unobserved groups through latent class models. Two shortcomings are noteworthy in respect to many studies cited above. All respondents are assumed to be homogeneous with regard to the decision rules used. In particular, all users are assumed to be utility maximizers. Second, attempts to identify homogeneous groups (latent classes) of users rely solely on empirical classification through goodness-of-fit measures. Therefore, behavioral differences across segments are difficult to discern and interpret directly. This study aims to address those issues by postulating the presence of behaviorally based segments having distinct decision rules as discussed later in this paper.

DATA DESCRIPTION

The data for this study are based on household surveys of 985 workers from eight zones in Chennai City. Respondents were selected randomly, and face-to-face interviews were conducted to obtain data on their work trips and the related sociodemographic variables.

The data collected with regard to mode choice included the mode chosen to work; vehicle ownership of two-wheelers, four-wheelers, and bicycles; users' ratings of different modes based on subjective factors; and access to public transport. In addition, data were obtained on activity characteristics such as ridesharing and en route shopping frequency and sociodemographic factors such as age, gender, income, and household size. Data on the presence of children and the number of nonworkers in the household were also elicited.

Descriptive statistics from the sample are as follows. The sample values of household size (4.37), percentage of males in the workforce (85%), and average age (36.9) are reasonably representative of the average population values: household size is 4.51, 78% of males are in the workforce, and average age of workers is 38 years. The average income (Rs. 16,185) in the sample is also similar to values of the population reported for Chennai (*25*). The average vehicle ownership per household in the sample is about 1.30 versus 1.44 based on vehicle registration data. The average distance to work is about 10.53 km.

The mode share of two-wheelers in the sample was nearly 42%, and the share of car use for work trips was about 6%. The overall mode share of public transport was 35.94%, with bus and train accounting for 20.1% and 15.84%, respectively. Nearly 9% of respondents reported the use of other IPT modes (e.g., auto rickshaw, share auto) and 6% reached their workplace by walking or by bicycle. The sociodemographic variables and aggregate mode shares were found to be reasonably representative for the given zones based on data in a larger earlier study (*25*).

Users were also asked to provide a rating on a 5-point scale with regard to comfort, reliability, flexibility of departing at any time, flexibility of access to multiple destinations, safety, and stress of various modes. The personal vehicle was given the highest rating on all but three factors, namely, safety, stress, and cost. Bus is ranked the lowest on all factors except cost, safety, and flexibility of multiple destinations. The train was rated lower than personal vehicle on comfort, reliability, and flexibility (departure time and multiple locations), but was rated better on safety, stress, and costs than the personal vehicle. Intermediate public transport (auto rickshaws) was rated better on convenience and reliability but was given the lowest rating on safety and cost.

The following observations are made on the basis of the descriptive statistics: First, two-wheeler ownership is significantly more than car ownership (1.11/household versus 0.19/household). The utility and disutility components of these two modes differ considerably (comfort, safety, exposure to congestion, etc.). Thus, the behavior of mode choice may differ substantially from that reported in other empirical contexts in which most workers own a car.

Second, a significant number of workers may have vehicles in their households, but no access to them (households with fewer vehicles available than workers is 29%) and are referred to as the semicaptive segment. Nearly 22% of respondents have no vehicle in the household or no driving knowledge and are referred to as captive users. Differences in mode shares of public transport are observed between noncaptive (households with more vehicles than workers), semicaptive, and captive groups. The public transport shares for the three groups are 21%, 36%, and 70% respectively. The alternatives available to semicaptive and captive groups suggest that their choice process will be somewhat constrained compared with that of the noncaptive group. Their responsiveness to modal characteristics may also be limited by the absence of sufficient alternatives.

Third, in regard to availability and access to public transportation, the city has an extensive bus network and a moderate-sized rail network that together serve nearly 3.6 million person trips per day. In the sample, the train and bus networks appear to be reasonably accessible to most users (75% of respondents reported residing within 0.5 km of a bus stop and nearly 61% within 1 km from a railway station). Despite the high level of physical accessibility to public transit modes, comfort and convenience may assume importance in the context of severe crowding in public transport modes. In such circumstances, it is unclear whether and to what extent disutility minimization may be invoked vis-à-vis utility maximization in selecting the mode of travel.

In that context, this study hypothesizes that at least some users will choose disutility minimization as the basis for selecting mode of travel to work. This hypothesis is tested in the following sections by developing alternative models of pure utility maximization, pure disutility minimization, and a heterogeneous model with some utility maximizers and some disutility minimizers.

HETEROGENEOUS DECISION RULE MODEL STRUCTURE AND PRELIMINARY ANALYSIS

Description

The heterogeneous decision rule (HDR) model is based on the conjecture that decision makers can be segmented into two different groups that apply distinct decision rules in selecting the chosen mode. One set of mode-choice decision makers is considered to be made up of utility maximizers and the other set, disutility minimizers.

Because it is not known a priori which of the two rules is applied by a given decision maker, the decision rule used remains latent. The propensity of using these two rules is estimated by using a binary utility function that can help in differentiating between utility maximizers and disutility minimizers. The mathematical formulation of this model is presented below.

Specification and Estimation

Let decision makers be denoted by the index $i = 1, \dots, N$, the mode choice alternatives by $j = 1, \dots, J$.

Let $Y_i = 1$ if individual i uses utility maximization to select the chosen mode;

Let $Y_i = 0$ if individual i uses disutility minimization in selecting the chosen mode; and

Let $\delta_{ij} = 1$ if individual i chooses alternative j and 0 otherwise.

Let U_{ij} = utility of alternative j to individual i if he or she uses utility minimization and

Let W_{ij} = disutility of alternative j to individual i if he or she uses disutility minimization.

Naturally, the utility and disutility of different alternatives are unobserved by the analyst and can be represented as the sum of deterministic and random components. Following conventions, the deterministic and random components are specified as follows:

$$U_{ij} = V_{ij} + \epsilon_{ij}$$

$$W_{ij} = S_{ij} + \theta_{ij}$$

where

V_{ij} = systematic component of utility of mode j to individual i,
S_{ij} = systematic component of disutility of mode j to individual i,
ϵ_{ij} = random component of utility of mode j to individual i, and
θ_{ij} = random component of disutility of mode j to individual i.

It is assumed that the deterministic components of the utility and disutility are functions of attributes of the decision maker and the alternative modes being considered.

$$V_{ij} = f\left(Z_{1i}, X_{1ij}, \beta_1\right)$$

$$W_{ij} = g\left(Z_{2i}, X_{2ij}, \beta_2\right)$$

where

Z_{1i} and Z_{2i} = vectors of decision-maker characteristics that affect the systematic utility and disutility terms,
X_{1ij} and X_{2ij} = vectors of modal attributes of mode j that affect the systematic utility and disutility terms, and
β_1 and β_2 = vectors of parameters influencing the systematic utility and disutility terms.

For convenience and as per standard practice, a linear-in-parameters form is assumed for these deterministic components of utility and disutility, respectively.

To keep the model structure simple, intuitive, and analytically tractable, it is assumed that the error terms ϵ_{ij} and θ_{ij} are independently and identically Gumbel distributed across alternatives and observations. This simplifying assumption is made given the interest in testing whether the hypothesis of different decision rules is supported by the empirical data. However, this assumption can be relaxed in a straightforward fashion in further work.

With these assumptions and notations, the probability of selecting a given mode and the log likelihood can be computed as follows:

For utility maximizers, the probability of choice of an alternative j by individual i, $P_{\text{um}i}(j)$, is given by the standard logit equation.

$$\Pr\left(\text{individual } i \text{ chooses mode } j \middle| \text{utility maximizing rule is used}\right)$$
$$= P_{\text{um}i}\left(j\right) = \frac{\exp\left(V_{ij}\right)}{\sum_k \exp\left(V_{ik}\right)} \quad (1)$$

For disutility maximizers, the user is assumed to select the alternative that has the smallest disutility.

$$\Pr\left(\text{individual } i \text{ chooses mode } j \middle| \text{disutility minimizing rule is used}\right)$$
$$= \Pr\left(W_{ij} \le W_{ik}\right) \text{ for all } k \ne j$$

The probability of the choice of an alternative can be derived using DeMorgan's laws as follows.

To illustrate, consider the six-alternative example used in this study. Subscript i is dropped for notational clarity.

$$\Pr\left(\text{individual } i \text{ chooses alternative } j \middle| \text{disutility minimization}\right)$$
$$= P_{\text{dm}i}\left(j\right) = \text{probability}\left(\text{alternative } j \text{ has a lower disutility than other alternatives}\right) = \Pr\left(W_j \le \text{all alternatives } W_k\right)$$
$$= 1 - \Pr\left(W_j \ge \text{disutility of at least one of the other alternatives}\right)$$
$$= 1 - \Pr\left\{\cup_k \left[W_j \ge W_k\right]\right\} \text{ for all } k \text{ distinct from alternative } j.$$

The above union event can be expanded using elementary probability theory in regard to the intersection of elementary events as follows:

$$\begin{aligned}
&= 1 - \sum \Pr\left(W_j \ge W_k\right) + \sum \Pr\left(W_j \ge W_k \text{ and } W_j \ge W_l\right) \\
&\quad - \sum \Pr\left(W_j \ge W_k \text{ and } W_j \ge W_l \text{ and } W_j \ge W_m\right) \\
&\quad + \sum \Pr\left(W_j \ge W_k \text{ and } W_j \ge W_l \text{ and } W_j \ge W_m \text{ and } W_j \ge W_n\right) \\
&\quad - \sum \Pr\left(W_j \ge W_k \text{ and } W_j \ge W_l \text{ and } W_j \ge W_m \text{ and } W_j \ge W_n \right. \\
&\quad \left. \text{and } W_j \ge W_o\right)
\end{aligned} \quad (2)$$

where k, l, m, n, and o represent indexes of the alternatives that are distinct from each other and are distinct from the chosen alternative j.

Each term inside the summation above represents the standard utility maximization probability. For instance, $\Pr(W_j \ge W_k)$ can be expressed as $\exp(W_j)/[\exp(W_j) + \exp(W_k)]$ and $\Pr(W_j \ge W_k, W_l, W_m) = \exp(W_j)/[\exp(W_j) + \exp(W_k) + \exp(W_l) + \exp(W_m)]$. In a similar manner, all other terms inside the summation can be computed using MNL expressions with a suitable number of alternatives.

Equations 1 and 2 denote the conditional probability of choice given that the individual maximizes utility and minimizes disutility, respectively. However, the decision rule used actually is latent and is not directly observed.

To quantify the propensity of using the utility maximizing versus disutility minimizing rules, a binary choice structure is assumed. Let R_i represent a continuous random variable that captures the propensity of individual i to use the utility maximizing rule. Whenever this propensity exceeds a threshold, it is assumed that the individual will apply the utility maximizing decision rule. Otherwise, the disutility, minimizing choice rule is invoked. Without loss of generality, the threshold can be taken as zero, by specifying a constant in the deterministic component of R_i. Thus, the correspondence between the underlying continuous propensity R_i and the decision rule used Y_i can be stated as $Y_i = 1$ if and only if $R_i > 0$ and $Y_i = 0$ otherwise. The random propensity corresponding to a decision rule R_i is assumed to consist of the deterministic term Q_i (which is a function of user characteristics) and error term η_i, which is independent and identically distributed logistically across observations. The deterministic term of the propensity to select a decision rule is assumed to be affected by the vector of attributes of the decision maker X_{3i} and the associated vector of parameters denoted by β_3.

With these distributional assumptions, the probability of choosing the two rules is given by

$$\begin{aligned}
P_{\text{UM}}\left(i\right) &= \Pr\left(\text{individual } i \text{ uses utility maximization}\right) \\
&= \Pr\left(Q_i + \eta_i \ge 0\right) = \exp\left(Q_i\right)/\left[1 + \exp\left(Q_i\right)\right] \\
P_{\text{DM}}\left(i\right) &= \Pr\left(\text{individual } i \text{ uses disutility minimization}\right) \\
&= \Pr\left(Q_i + \eta_i \le 0\right) = 1/\left[1 + \exp\left(Q_i\right)\right]
\end{aligned} \quad (3)$$

Because the actual rule used by the individual is unobserved, the unconditional probability of choosing alternative *j,* for a given individual *i,* can be written in relation to the conditional probabilities of modal choice and probability of choosing the two decision rules as

$$P_{ij} = P_{\mathrm{UM}}(i) P_{\mathrm{um}i}(j) + P_{\mathrm{DM}}(i) P_{\mathrm{dm}i}(j) \tag{4}$$

The likelihood (L) and the log likelihood (LL) of the sample of *N* observations can then be written as

$$\mathrm{L} = \prod_i \prod_j P_{ij}^{\delta_{ij}}$$

and

$$\mathrm{LL} = \log(\mathrm{L}) = \sum_i \sum_j \delta_{ij} \log\left[P_{\mathrm{UM}}(i) P_{\mathrm{um}i}(j) + P_{\mathrm{DM}}(i) P_{\mathrm{dm}i}(j)\right] \tag{5}$$

where $\delta_{ij} = 1$ if individual *i* chose alternative *j* and = 0 otherwise.

The vectors of parameters β_1, β_2, and β_3 that affect the model can be estimated using the maximum likelihood technique in view of its desirable asymptotic properties of unbiasedness, consistency, and efficiency.

FINAL HETEROGENEOUS DECISION RULE MODEL, RESULTS, AND DISCUSSION

Preliminary Evidence of Heterogeneity in Decision Rules

To assess the possibility of heterogeneous decision segments, the following four models are estimated for the entire data set: (*a*) homogeneous utility maximization model [multinomial logit (MNL)], (*b*) homogeneous pure disutility minimization model [reverse multinomial logit model (RMNL)], (*c*) latent class model (LCM) with two utility maximizing segments, and (*d*) HDR model consisting of a utility maximizing and a disutility minimizing segment. A total of 948 observations were used after missing data were discarded for this baseline specification.

The variables in the baseline model included vehicle ownership, travel time, and cost. The log likelihoods of the homogeneous MNL and RMNL models were −1034.5 and −1037.9 respectively with 14 parameters each. The HDR model and LCM model had log likelihoods of −979.5 and −994.7, with 30 and 27 parameters respectively.

The two homogeneous models can be obtained as a special case of the HDR model by constraining the probability of the utility maximization segment to 0 and 1 respectively. The chi-squared test confirms that the hypothesis of homogeneous decision rule (MNL versus HDR) must be rejected ($\chi^2_{\mathrm{observed}} = 2(55) = 110 > \chi^2_{\mathrm{critical}} = 26.3$) at the 95% confidence level. Similarly, the MNL and RMNL models are also to be rejected compared with the LCM model on the basis of chi-squared and Horowitz tests respectively. Results indicate that the HDR model is to be preferred over the LCM model at the 95% confidence level.

Final Model Specification

The results above are consistent with the hypothesis that there are two distinct segments in the population with different decision rules. Therefore, investigating differences in choice behavior across these hypothesized user segments is important from both theoretical and practical standpoints. Further, identifying the factors that differentiate users belonging to the two segments will be useful in developing and targeting suitable policies for each segment.

The following questions arise in this context. Is the sensitivity to modal characteristics such as travel time and cost different across the segments? What is the role of subjective factors in mode choice for each segment? Does the accessibility to public transport have a greater influence on the disutility minimizing segment? How influential are activity characteristics in determining the mode choice of the two segments? Which socioeconomic and demographic user characteristics can effectively explain the decision rule selected? To address these issues, the baseline HDR model is refined by including subjective factors, activity characteristics, and accessibility variables.

Performance of HDR Model in Calibration and Validation Data Sets

The best-fitting model is shown in Table 1. The proposed HDR model provided a log likelihood of −703.62 and a likelihood ratio index (rho-squared) of 0.445 for the calibration data consisting of 707 observations. Thus, the model provides a reasonably good fit with observed choice data. Pure MNL, pure RMNL, and LCM models were also calibrated with the same specification as this model. The corresponding log likelihood values were −734.41, −742.01, and −732.32 (LCM is not shown in the table) respectively. The results again highlight that the alternative models must be rejected in favor of the proposed HDR model even with the richer specification of explanatory variables.

The performance of the proposed model was also evaluated using a prediction data set with 241 observations (Table 2). The predicted log likelihood from the calibration model was −253.99 and the goodness of fit (likelihood ratio index ρ^2) was 41.18%. The corresponding statistics for the other models are MNL (LL = −257.61, ρ^2 = 40.34%), RMNL (LL = −263.11, ρ^2 = 39.07%), and LCM was (LL = −272.79, and ρ^2 = 36.83%), once again confirming the better predictive ability of the HDR model.

The practical significance of the HDR model can be best understood by comparing the coefficients of the MNL (homogeneous decision model) and the HDR model. Some variables are insignificant in the MNL model but are significant for at least one segment in the HDR model. For instance, the MNL fails to recognize the effect of the number of cars on car and IPT mode shares, the role of flexibility of personal vehicle, and the effect of en route activities (work-related trip frequency). The lack of significance is understandable because these factors affect only one of the two segments in the HDR model. As a result, a homogeneous model may fail to consider policy measures that may be particularly effective in some segments.

At the other extreme, the homogeneous model may overestimate the impact of certain factors and policies by assuming that all respondents are affected. For instance, the effect of no driving knowledge and accessibility of railway station at home and at work is likely to be overestimated by assuming homogeneity, although these variables affect only the disutility minimizing segment. Thus, the homogeneous decision rule model may either overstate or underestimate the impact of certain variables.

Difference in Choice Behavior Across Utility Maximizers and Disutility Minimizers

The average probability of belonging to the utility maximizing segment is about 32.59%. This finding indicates that a majority of

TABLE 1 Comparison of HDR, MNL, and RMNL Coefficients

	DM		UM					
	HDR (disutility coefficient)		HDR (utility coefficient)		MNL (utility coefficient)		RMNL (disutility coefficient)	
Variable Description	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Alternate specific constant two-wheeler	–0.54	–3.94	3.78	8.74	1.14	11.22	–0.90	–10.19
Alternate specific constant four-wheeler	–0.08	–0.98	0.06	0.20	0.08	0.96	–0.04	–0.48
Alternate specific constant train	2.63	12.54	–1.73	–3.12	–1.37	–10.01	2.06	22.19
Alternate specific constant other (IPT)	1.84	10.33	–2.73	–0.45	–0.28	–1.85	1.38	14.46
Alternate specific constant nonmotorized	–1.11	–5.01	0.06	0.20	0.55	3.34	–0.17	–1.60
Variation in Travel Time Sensitivity								
Travel time (two-wheeler, four-wheeler, IPT)	0.02	1.33	–0.08	–1.29	–0.03	–1.11	0.03	2.79
Travel time (nonmotorized)	0.12	2.33			–0.07	–1.78	0.03	0.74
Travel time (bus, train)	0.04	2.43			–0.03	–4.39	0.02	4.17
Variation in Cost Sensitivity								
Cost of public transport (distance ≤ 8 km)	0.64	8.45			–0.38	–6.29	0.10	2.90
Cost of IPT (distance ≤ 8 km)	0.05	1.41			–0.03	–0.62	–0.003	–0.08
Cost of two-wheeler (distance ≤ 8 km, no vehicle)	0.44	2.7	–0.09	–1.46	–0.28	–8.45	0.10	6.36
Cost of two-wheeler (distance > 8 km, no vehicle)	0.13	2.08	–0.05	–1.30	–0.11	–2.09	0.08	6.51
Cost of four-wheeler (distance ≤ 8 km, no vehicle)	5.45	1.48			–0.06	–0.14	0.02	0.76
Cost of four-wheeler (distance > 8 km, no vehicle)	0.02	1.46			–0.02	–0.74	0.01	0.42
Vehicle Ownership and Driving Knowledge								
No driving knowledge (bus, train)	–1.13	–4.63			1.24	5.60	–0.72	–4.78
Vehicle ownership of two-wheeler only (train)			0.25	0.75				
Number of four-wheelers (four-wheeler, IPT)			3.48	7.65				
Subjective Factors								
Reliability rating of train (train)	–0.5	–11.14	0.49	6.47	0.50	16.34	–0.31	–11.57
Indicator variable = 1 if safety of traveling in train is higher than personal vehicle (train)	–0.59	–3.00			0.61	4.10	–0.49	–4.38
Indicator variable = 1 if stress of traveling in bus is higher (two-wheeler, train)	–0.42	–2.53			0.20	1.51	–0.16	–1.60
Indicator variable = 1 if flexibility of multiple destinations of private vehicle is higher than bus and IPT (two-wheeler)	–0.39	–1.89	1.42	3.15				
Role of Accessibility								
Indicator variable = 1 if distance of local train station to office < 1,000 m	–0.71	–3.45			0.54	3.45	–0.29	–2.44
Indicator variable = 1 if reaching local railway station is easy (train)	–0.87	–4.76			0.64	4.62	–0.35	–3.34
Indicator variable = 1 if distance of home bus stop < 500 m (train, IPT)	0.64	4.94			–1.66	–14.61	–0.08	–1.19
Activity Characteristics								
Indicator variable = 1 if a shopping store is available near the house or the place of work (four-wheeler, IPT)			0.15	1.43				
Indicator variable = 1 if the user either frequently travels on work-related trips during office hours or returns home for lunch (two-wheeler, four-wheeler)			1.25	1.84				

(continued)

TABLE 1 *(continued)* **Comparison of HDR, MNL, and RMNL Coefficients**

	DM		UM					
	HDR (disutility coefficient)		HDR (utility coefficient)		MNL (utility coefficient)		RMNL (disutility coefficient)	
Variable Description	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Utility 3 (membership)								
Alternate specific constant (utility maximization)	−1.71	−7.49						
Indicator variable—high household income (>$25,000) (utility maximization)	0.58	1.34			0.75	2.47 (4w)	−0.47	−1.91 (4w)
Indicator variable = 1 if there are kids below age 5 (utility maximization)	0.97	3.08						
Indicator variable = 1 if work time is not flexible (disutility minimization)	1.71	3.75			0.83	5.27 (2w,4w)	−0.65	−5.36 (2w,4w)
Indicator variable = 1 if worker belongs to the choice sector (utility max)	2.41	9.79						
LL (0)			−1,266.77		−1,266.77		−1,266.77	
LL (convergence)			−703.62		−734.41		−742.012	
Likelihood ratio index (ρ^2)			0.445		0.420		0.414	
No. of observations			707		707		707	

respondents in the sample use disutility minimization rather than utility maximization in selecting their means of travel to work.

The average mode shares show that nearly two-thirds of respondents in the utility maximization group choose personal vehicles (55.38% for two-wheelers and 8.07% for cars). The public transport mode share is about 28%, and the other modes (nonmotorized and IPT) make up a nearly 8% share. In sharp contrast, among the disutility minimization segment, the public transport share is the largest (about 46%), followed by personal vehicle modes (nearly 35% with 32% two-wheeler and 2.6% car). Note the sharp reduction in both two-wheeler (22%) and car shares (nearly 5.5%) in the disutility minimization group. Furthermore, the share of nonmotorized and IPT in this segment, about 21%, is quite substantial compared with the UM segment. The preference for IPT modes is particularly strong in the disutility minimization segment with a share of 13.92% in contrast to the 0.15% in the UM group. These results suggest that UM users may value personal mobility and privacy, and DM users may also shift from public modes to semiprivate modes (such as intermediate public transport), which offer greater flexibility and comfort. Thus, the DM users are not necessarily captive to public transport modes.

Table 1 presents the coefficients of the deterministic utility (V) and disutility components (S) for the HDR model. A positive coefficient for a variable in utility maximization implies that the utility increases as the variable increases; a positive disutility coefficient implies that the disutility increases with the variable.

A comparison of the alternative specific constants reveals a greater preference for the two-wheeler among utility maximizers than among disutility minimizers. The constant associated with nonmotorized modes is larger for the disutility minimization group, which may be a reflection of the vehicle availability in this group. These results may be attributed to the constraints and perceived inconvenience of public transport, IPT, and nonmotorized modes. Another interesting observation is that the perceived disutility of IPT (after accounting for the effect of other factors) is more than that for the train for the UM segment and vice versa for the DM segment. The findings point to the greater value placed on personal mobility in the utility maximization segment than in the disutility minimization segment.

TABLE 2 Log Likelihood and Mode Shares in Prediction Data

Mode	HDR Mode Share	MNL Mode Share	RMNL Mode Shares	LCM Mode Shares	Actual Mode Shares
Two-wheeler	40.94	42.21	42.08	38.41	43.57
Four-wheeler	4.95	4.89	5.06	5.16	6.22
Bus	22.32	21.07	20.8	17.48	18.67
Train	16.66	16.55	15.98	13.34	16.6
IPT	9.65	9.79	9.96	20.32	7.88
Nonmotorized	5.49	5.49	6.12	5.29	7.05
LL (0)	−431.81	−431.81	−431.81	−431.81	
LL (pred)	−253.99	−257.61	−263.11	−272.79	
Predicted ρ^2 (%)	41.18	40.34	39.07	36.83	

Travel Time and Cost Sensitivity

Findings also highlight some salient differences in sensitivity to travel time and cost across the two decision segments. For instance two-wheeler and public transport cost sensitivity is particularly high in the disutility segment, whereas it is insignificant in the utility maximizing group. Note also that the disutility minimizing group is not sensitive to the cost of IPT and the car. Further, the two-wheeler sensitivity for this segment decreases significantly with distance.

In regard to travel time, the significant difference is in the sensitivity of disutility minimizers to nonmotorized and public transit modes, whereas utility maximizers are not sensitive to the travel times of these modes. In addition, sensitivity to travel time of nonmotorized modes is much higher (–0.12) than for other modes. In contrast, the public transport and nonmotorized travel time coefficients are insignificant for the UM segment

The results highlight the nonlinear variation of cost sensitivity with increasing trip length. A similar effect of reduced sensitivity is also seen in the case of UM (–0.09 and –0.05 for trips shorter than and longer than 8 km). However, the cost coefficient in UM for other modes was insignificant.

Vehicle Availability

The following variables were found to be significant determinants of choice. Workers from the UM segment belonging to households with more cars exhibit a greater propensity to choose car and IPT modes over other alternatives. This may be attributed to the greater affordability of personal vehicles and preference for unconstrained mobility among these users. In the UM segment, workers from households with only two-wheelers are more likely to select the train, which may reflect the resource sharing constraints in such households. Disutility minimizers with no driving knowledge are more likely to prefer bus or train over nonmotorized and IPT modes. Thus, captivity plays a more significant role in public transport choice in the disutility minimizing segment.

Role of Subjective Factors

The preference for personal vehicles is attributable in part to the greater flexibility they afford to reach multiple destinations in both segments. However, this effect was much more influential in the case of UM (1.42) than DM (0.39). The choice of public transport modes is also affected by subjective factors. For instance, both groups are more likely to select train if the perceived reliability is high. But the effect of train reliability is nearly the same in both segments. Other subjective factors such as stress and safety also affect the choice in the DM segment. Train is preferred by disutility minimizers who perceive the personal vehicle to be less safe than the train. Similarly, respondents who reported higher stress levels for bus (possibly due to overcrowding) are more likely to prefer the train or two-wheeler. Thus, the DM segment appears to place more emphasis on the inconvenience perceived in available modes, whereas the UM segment attaches greater importance to flexibility and value offered particularly by personal modes.

Effect of Accessibility and Activity Characteristics

The effect of access to public transport was found to be significant only for the disutility minimization segment, perhaps because of its larger share in the sample and its greater intensity of use of public transport modes. Access to railway stations near home and access at work were both found to be significant for this group in the anticipated direction. Further, the presence of a bus stop near home was a strong deterrent to the use of IPT and train modes in this segment.

Work-related and en route activities appear to be a significant determinant of personal vehicle choice in the utility maximization group. The presence of a grocery store near home correlated positively with the propensity to use a car or IPT, which may facilitate en route shopping stops unlike public modes. Respondents who make frequent work-related trips during lunch or after office hours were also more likely to use a personal vehicle in this segment. Thus, the UM segment appears to place a premium on the flexibility to perform other activities and trips while selecting the commute mode.

Factors Influencing Selection of Decision Rule

The following variables were found to play an important role in the propensity to use the utility maximizing decision rule. The alternative specific constant is negative, suggesting a significant propensity to be a disutility minimizer among workers in Chennai City, which is borne out by the average segment shares noted earlier in this section. The propensity to belong to the utility maximizing segment increases as income increases, which is consistent with intuition. The workers belonging to the noncaptive segment are more likely to be utility maximizers. Users with small children (<5 years old) and those with flexible work hours are also more likely to be utility maximizers, highlighting the greater role of time and interpersonal constraints in mode choice.

Application of HDR Models for Policy Analysis

To assess the performance in regard to policy evaluations, the role of two policy and planning scenarios was analyzed using the HDR, MNL, and RMNL models. The mode choice probabilities and aggregate shares were compared under the following scenarios: (*a*) increase in travel time by 40% of road-based modes and (*b*) increase in cost of two-wheeler, four-wheeler, and IPT modes (bus cost is assumed to be fixed at current levels as a result of regulatory issues). These two scenarios are intended to study the effect of a significant increase in congestion and fuel price from the current scenario. For each model, the predicted modal share in each policy scenario of interest is computed as shown in Table 3.

With the increase in travel time, almost all models lead to nearly the same mode share for car, train, and nonmotorized modes in the anticipated directions. However, there are significant differences in the mode shares of bus and two-wheeler. In particular, the homogeneous models, MNL and RMNL, estimate a 0.1% to 0.6% increase in two-wheeler share when travel time increases by 40%, which appears to be counterintuitive, whereas the HDR estimates a nearly 1.3% decline. The decline in bus share is sharper in the homogeneous model (nearly 5.6%–6%) compared with a 4% reduction estimated by the HDR model. All models capture an increased mode share of train by about 4.5% (because it is not affected by congestion) and a slight increase in IPT (nearly 1%) with such a significant travel time increase of road-based modes.

There are clear differences in the impact of travel time across the decision segments (Table 4). The travel time increase leads to a 9% reduction in bus share among DM, and an increase of nearly 5% for

TABLE 3 Policy Analysis Results

Mode	Travel Time Increase by 40%			PV[a] and IPT Travel Cost Increase by 40%			Actual Mode Share
	HDR	MNL	RMNL	HDR	MNL	RMNL	
Two-wheeler	40.64	42.38	41.91	32.59	32.3	34.68	41.77
Four-wheeler	4.99	5.33	5.39	5.46	4.77	5.22	6.01
Bus	16.13	14.68	14.31	26.48	25.74	23.73	20.25
Train	21.05	21.01	21.27	18.77	19.15	17.94	16.46
IPT	10.71	10.35	10.2	10.28	11.55	12.09	9.49
Nonmotorized	6.48	6.25	6.92	6.43	6.48	6.34	6.01

[a]PV = private vehicle.

train, 2% for two-wheelers, and nearly 1% each for nonmotorized and IPT modes. In contrast, travel time increase results in a decline of 5% and 1% in two-wheeler and car shares respectively and nearly 3% increase in bus and train shares. These differences are a reflection of the greater value of travel time for personal vehicle (PV) users, which results in a shift to other modes, whereas the disutility minimizers seek to shift from bus to other modes with increasing travel time.

For the scenario of cost increase, both homogeneous decision rule models underestimate the share of some modes and overestimate the share of others. For instance, car and bus shares are underestimated by nearly 0.25% to 2.7% and IPT shares are overestimated by about 1.2% to 1.8% relative to the HDR model. The homogeneous decision models exhibit mixed trends in estimating the two-wheeler and nonmotorized shares. The pure disutility minimization model overestimates two-wheeler share after cost increase, whereas the utility maximization model underestimates this share. In other words, the pure UM (MNL) model overestimates the adverse impact of a cost increase on two-wheeler share. In contrast to two-wheeler share, the utility maximization model overestimates train share and the RMNL underestimates compared with HDR.

Unlike the effect of travel time, the effect of cost on the UM group is smaller. The personal vehicle shares decline by about 4% for two-wheelers and 0.6% for cars, with little change in the shares of other modes. However, a much larger influence of cost increase is observed in the DM segment. There is a nearly 11.5% reduction in two-wheeler share and 0.5% reduction in car use. The shift is observed from personal vehicle to public modes (bus increases by 7%, train by nearly 3%, and nonmotorized and IPT modes by about 1%). These findings suggest that the utility maximization group is much less elastic to price than the disutility minimization segment.

CONCLUSIONS

This study investigates the possibility of heterogeneity in decision rules in the context of work-trip mode choice. Specifically, the presence of two decision segments, namely, utility maximizing and disutility minimizing segments, is hypothesized. The choice behavior of these segments is quantified using MNL and reverse MNL models, and the segment membership propensity is quantified using a binary logit structure. The resulting heterogeneous decision rule model is estimated using the maximum likelihood technique.

The empirical results from the calibration data show that the proposed heterogeneous decision rule model outperforms homogeneous specifications (pure utility maximization and pure disutility minimization). Further, it is also superior to a latent class model with two utility maximizing segments that also outperforms the homogeneous models. These results are observed for a baseline specification involving only modal attributes and extended specifications involving subjective factors and activity characteristics. The findings are also corroborated by the better predictive ability of the proposed HDR model with a holdout data set. Thus, the results provide significant evidence of the simultaneous presence of utility maximizing and disutility minimizing behavior among respondents. In addition, the results indicate that the utility maximization and disutility minimization represent distinct behaviors. This indicates the absence of

TABLE 4 Utility Maximization and Disutility Minimization Mode Shares Under Different Policy Scenarios

Mode	Travel Time Increase by 40%		PV and IPT Travel Cost Increase by 40%		Existing Scenario	
	UM Mode Shares	DM Mode Shares	UM Mode Shares	DM Mode Shares	UM Mode Shares	DM Mode Shares
Two-wheeler	49.98	34.84	51.64	21.11	55.38	32.65
Four-wheeler	7.00	2.66	8.71	2.00	8.07	2.57
Bus	17.17	16.62	15.68	32.85	14.42	25.66
Train	16.99	23.89	15.55	21.88	14.14	19.02
IPT	0.14	15.14	0.16	14.91	0.15	13.92
Nonmotorized	8.73	6.84	8.25	7.24	7.84	6.17

symmetry of the error structure in this choice context. Therefore, disregarding the heterogeneity in decision rules when present can lead to erroneous forecasts and biased policy evaluations.

In regard to substantive findings, there are clear differences in mode choice behavior across the two segments at various levels. These include differences in aggregate modal shares, intrinsic preference for different modes, sensitivity to modal attributes, role of subjective factors, and the effect of activity patterns and accessibility. The utility maximizing group is more sensitive to travel time, whereas the disutility minimizing segment is more sensitive to cost. Activity characteristics (en route shopping, work-related trips, etc.) and subjective factors related to flexibility and mobility have a more pronounced effect on the choice of utility maximizers. In contrast, access to public transportation and subjective factors such as stress, safety, and reliability are significant determinants of mode choice for disutility minimizers. These differences are also reflected in the estimated mode shares under illustrative policy scenarios.

The key variables that affect the propensity to apply the utility maximization principle include high income, flexible time at work, presence of small children at home, and noncaptive status (vehicle-to-worker ratio is at least 1). These findings have important implications for the evaluation of new transportation infrastructure projects (e.g., metro rail) and the analysis of transportation control measures (TCMs) aimed at congestion mitigation and transit improvement.

This study can be extended in the future to address the following interesting research issues: To what extent may other decision rules, such as conjunctive, disjunctive, and satisficing rules, be applied by at least some users in the mode choice context? What is the role of unobserved heterogeneity (random taste variation) in the context of the HDR model? Specifically, the presence of heterogeneity at multiple levels is of interest (*a*) across decision rules, (*b*) across latent classes within each decision rule, and (*c*) unobserved heterogeneity within each latent class. Are such heterogeneity and disutility minimization relevant in developed countries versus developing countries and to what extent? Investigating and identifying policies tailored to specific decision segments will enable more effective implementation of TCMs.

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REFERENCES

1. Anderson, S. P., and A. De Palma. Reverse Discrete Choice Models. *Regional Science and Urban Economics,* Vol. 29, 1999, pp. 745–764.
2. Misra, S. Generalized Reverse Discrete Choice Models. *Quantitative Marketing and Economics,* Vol. 3, No. 2, 2005, pp. 175–200.
3. Ben-Akiva, M., and S. R. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand.* MIT Press, Cambridge, Mass., 1985.
4. Cervero, R. Built Environments and Mode Choice: Toward a Normative Framework. *Transportation Research Part D,* Vol. 7, 2002, pp. 265–284.
5. Manski, C. The Structure of Random Utility Models. *Theory and Decision,* Vol. 8, 1977, pp. 229–254.
6. Bhat, C. R. Incorporating Observed and Unobserved Heterogeneity in Urban Work Mode Choice Modeling. *Transportation Science,* Vol. 34, No. 2, 2000, pp. 228–238.
7. Hess, S., M. Bierlaire, and J. W. Polak. A Systematic Comparison of Continuous and Discrete Mixture Models. *European Transport,* Vol. 37, 2007, pp. 35–61.
8. Algers, S., S. Hansen, and G. Tegner. Role of Waiting Time, Comfort, and Convenience in Modal Choice for Work Trip. In *Transportation Research Record 534,* TRB, National Research Council, Washington, D.C., 1975.
9. Koppelman, F. S., and P. K. Lyon. Attitudinal Analysis of Work/School Travel. *Transportation Science,* Vol. 15, 1981, pp. 233–254.
10. Johansson, M., T. Heldt, and P. Johansson. Effects of Attitudes and Personality Traits on Mode Choice. *Transportation Research Part A: Policy and Practice,* Vol. 40, No. 6, 2006, pp. 507–525.
11. Phanikumar, C. V., and B. Maitra. Valuing Urban Bus Attributes: An Experience in Kolkata. *Journal of Public Transportation,* Vol. 9, No. 2, 2006, pp. 69–87.
12. Bhat, C. R. Covariance Heterogeneity in Nested Logit Models: Econometric Structure and Application to Intercity Travel. *Transportation Research Part B,* Vol. 31, No. 1, 1997, pp. 11–21.
13. Cascetta, E., and A. Papola. Random Utility Models with Implicit Availability/Perception of Choice Alternatives for the Simulation of Travel Demand. *Transportation Research Part C,* Vol. 9, 2001, pp. 249–263.
14. Zhang, J., H. Timmermans, A. Borgers, and D. Zhang. Modeling Traveler Choice Behavior Using the Concepts of Relative Utility and Relative Interest. *Transportation Research Part B,* Vol. 38, 2004, pp. 215–234.
15. Ben-Akiva, M., D. McFadden, K. Train, J. Walker, C. R. Bhat, M. Bierlaire, D. Bolduc, A. Boersch-Supan, D. Brownstone, D. S. Bunch, A. Daly, A. D. Palma, D. Gopinath, A. Karlstrom, and M. A. Munizaga. Hybrid Choice Models: Progress and Challenges. *Marketing Letters,* Vol. 13, No. 3, 2002, pp. 163–175.
16. Beckman, J., and K. Goulias. Immigration, Residential Location, Car Ownership, and Commuting Behavior: A Multivariate Latent Class Analysis from California. *Transportation,* Vol. 35, No. 5, 2008, pp. 655–671.
17. Greene, W., and D. Hensher. A Latent Class Model for Discrete Choice Analysis: Contrasts with Mixed Logit. *Transportation Research Part B: Methodological,* Vol. 37, No. 8, 2003, pp. 681–698.
18. Shen, J., Y. Sakata, and Y. Hashimoto. *A Comparison Between Latent Class Model and Mixed Logit Model for Transport Mode Choice: Evidences from Two Datasets of Japan.* Graduate School of Economics and Osaka School of International Public Policy (OSIPP), Osaka University, Toyonaka, Osaka, Japan, Jan. 2006. www2.econ.osaka-u.ac.jp/library/global/dp/0605.pdf.
19. Fosgerau, M., and M. Bierlaire. A Practical Test for the Choice of Mixing Distribution in Discrete Choice Models. *Transportation Research Part B: Methodological,* Vol. 41, No. 7, 2007, pp. 784–794.
20. Pinjari, A. R., and C. R. Bhat. Nonlinearity of Response to Level-of-Service Variables in Travel Mode Choice Models. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1977,* Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 67–74.
21. Bhat, C. R. An Endogenous Segmentation Mode Choice Model with an Application to Intercity Travel. *Transportation Science,* Vol. 31, No. 1, 1997, pp. 34–48.
22. Timmermans, H. J. P. Non-Compensatory Decision Rules and Consumer Spatial Choice Behavior: A Test of Predictive Ability. *Professional Geographer,* Vol. 35, 1983, pp. 449–455.
23. Timmermans, H. J. P., A. W. J. Borgers, and K. J. Veldhuisen. A Hybrid Compensatory-Noncompensatory Model of Residential Preference Structures. *Netherlands Journal of Housing and Environmental Research,* Vol. 1, No. 3, 1986, pp. 227–233.
24. Srinivasan, K. K., and H. S. Mahmassani. Role of Congestion and Information in Trip-Makers' Dynamic Decision Processes: An Experimental Investigation. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1676,* TRB, National Research Council, Washington, D.C., 1999, pp. 44–52.
25. Srinivasan, K. K., and P. V. L. Bhargavi. Longer-Term Changes in Mode Choice Decisions in Chennai: A Comparison Between Cross-Sectional and Dynamic Models. *Transportation,* Vol. 34, No. 3, 2007, pp. 355–374.

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