Integrating Household-Level Mode Choice and Modal Expenditure Decisions in a Developing Country

Multiple Discrete–Continuous Extreme Value Model

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This paper investigates two mode-related dimensions at the household level, namely, mode choice and modal use intensity (as reflected by modal expenditures). These dimensions are analyzed jointly in the context of Chennai city in India, by using a large disaggregate database consisting of more than 2,000 households. Specifically, the objectives of this study are to analyze mode choice decisions at the household level, to integrate mode choice and mode usage using a suitable model, and to analyze the effect of contextual factors relevant to developing countries on the mode choice propensity and mode use intensity. At the household level, the mode choice problem is a multiple discrete choice problem (multiple alternatives may be selected) in contrast to the singly discrete nature of the individual mode choice problem. Therefore, a multiple discrete–continuous extreme value model is formulated to integrate choice and usage, based on a coherent utility maximization framework. To the authors' knowledge, this study is the first to model mode choice as a multiple discrete choice problem. The results reveal that several unique and context-specific features in developing countries affect household-level mode choice significantly. Further, the mode use intensity of alternative modes is influenced by prior mode choice decisions, inertia, and user's perception of safety and congestion. The results have important planning and policy implications for transit improvement and congestion mitigation strategies.

Mode choice models play a pivotal role in the analysis of travel demand and evaluation of several transportation control measures including vehicle occupancy improvement, transit policy assessment, and congestion pricing. This study concentrates on analyzing mode choice at the household level of aggregation in the context of a developing country—namely, India.

There are three primary motivating factors for this study:

1. Capturing mode choice decisions at the household level of aggregation enables a more behavioral modeling approach compared with the standard mode choice model currently used at the person level of disaggregation.
2. Additional insights on mode selection can be obtained by jointly modeling mode choice decisions with the associated consumption decisions (expenditures per mode).
3. A number of context-specific factors affecting mode choice in developing countries that are different from those in developed countries remain to be investigated.

The first motivation is that there are significant advantages in modeling mode choice at the household level rather than at the individual level. At the household level, a significant share of multiple modes being collectively chosen by different household members is empirically observed (see the section on data description) and should be captured. Also, the household is the most basic group decision-making unit, where the members try to allocate their collective income to different modes, with a fixed cost and time budget constraint for travel. Thus, intrahousehold interactions that contribute to mode choice are best captured at the household level of aggregation, by using household attributes (e.g., family structure) or through individual-level proxies (e.g., number of workers returning home for lunch, presence of a nonworker).

The second motivation is that, although there have been many separate studies on mode choice and travel time and cost expenditures, very few studies have tried to model choice and consumption together by using a single modeling framework. Integrating these dimensions would provide a richer and more intuitive representation of activity-based factors such as interpersonal linkages in activity delegation, joint activity participation, and vehicle allocation, leading to improved policy predictions on air quality, congestion mitigation, and commuter safety. Furthermore, mode choice propensity can influence mode use intensity and vice versa. For instance, with increasing levels of intensity, nonlinear effects such as inertia and satiation can affect mode choice probabilities.

The final motivation for this study is that the mode choice scenario in developing countries is markedly different from that in developed countries. Developing countries have certain unique features such as mixed traffic flow, mixed land use, predominantly less per capita income compared with developed nations, greater nonworker availability at home, significant use of two-wheelers and availability of intermediate public transit (IPT), joint family structure, and availability of multiple modes with significant mode shares for each (in contrast to developed countries where the maximum trips are made using a personal vehicle). The role of these features on mode choice in developing countries has not been adequately studied in the literature.

The household-level mode choice decisions differ from individual-level mode choice models in the following respects. First, the

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household-level mode choice decisions are multiple discrete in nature (multiple alternatives may be chosen from the choice set at the same time). In contrast, the individual-level trip-based mode choice decision is often modeled using singly discrete (mutually exclusive alternatives) methods. Thus, for mode choice at the household level, it is essential to model the combined choice of various modes (by individual traveling members) as a multiple discrete choice problem. In other words, the dependent mode choice variable at the household level is the portfolio of modes chosen by the household. Second, household-level mode choice decisions involve allocation of monetary resources to travel (expenditures) by various modes. This variable is indicative of the mode usage propensity of the household, which influences and is influenced by mode choice decisions of all household members. These features are not sufficiently captured by the individual-level mode choice models that are widely used for planning applications.

In this context, this study pursues the following objectives:

- To analyze mode choice at the household level as a multiple discrete choice problem, as opposed to single discreteness-based analyses;
- To integrate the dimensions of mode choice and mode usage intensity by using a suitable model; and
- To investigate the effect of contextual factors (e.g., state dependence, attitudinal indicators, quality-of-service variables) relevant to developing countries (noted above) on household-level mode choice and mode usage.

These objectives were pursued by investigating two related decision dimensions: modes chosen by households and monetary expenditures on each of the chosen modes for a given household. These dimensions were modeled based on a large-scale database obtained from the Chennai Household Travel Survey (2004–2005) consisting of more than 2,000 households. A multiple discrete–continuous extreme value (MDCEV) model (*1*) was used to integrate the two related dimensions in a mutually consistent manner. To investigate the effects of contextual variables specific to developing countries on household-level mode choice, suitable hypotheses were created and tested through relevant variables in the proposed MDCEV model.

This paper makes the following distinct contributions to the existing literature on mode choice models, travel expenditure analysis, and developing-country studies: (*a*) Household-level mode choice is analyzed as a group decision-making, multiple discrete choice problem. To the authors' knowledge, this study is the first instance of mode choice being analyzed as a multiple discrete problem in the literature. (*b*) Mode choice and modal expenditures are integrated and analyzed by using a single model (MDCEV). (*c*) This paper identifies and analyzes the effect of substantive factors on mode choice in a developing country—in this case, India. (*d*) By analyzing travel cost expenditure as the mode usage component in MDCEV, this paper contributes to the literature on travel money allocation, where relatively fewer works exist compared with time-use studies. (*e*) Finally, this study investigates the role of factors such as inertia and inconvenience that influence the mode use intensity, in contrast to prior studies that capture these effects on choice propensity.

Further, this work is different from other MDCEV-based studies, which mainly capture satiation effects with given alternatives leading to the choice of other alternatives (*1*), whereas other sources of nonlinearity that contribute to diminishing marginal utilities are identified in this study.

The rest of this paper is structured as follows. The next section presents a review of existing relevant works in the literature and a summary of substantive gaps in them. The third section gives details about the data used for this study. The methodologic approach is discussed in the fourth section. The model estimation results and interpretation are presented in the fifth section, and the last section presents conclusions, assumptions, and directions for future research.

LITERATURE REVIEW

Although the literature related to mode choice, activity decisions, and time–cost budget is quite extensive, in the interest of space, the scope of this review is restricted to two streams that are most pertinent to this study.

Studies on Mode Choice

Several mode choice studies have investigated the effect of objective factors including in-vehicle time, out-of-vehicle time, transfers, travel cost, and travel frequency (*2–4*). In addition, subjective factors, perceptions, and attitudes relating to comfort, safety, and built environment also strongly influence passengers' mode selection decisions (*5–7*). With the advent of flexible modeling structures such as mixed logit (*8, 9*), recent studies demonstrate the ability to develop richer and more accurate forecasts by operationalizing these effects (*10*).

In contrast to developed countries, relatively fewer insights are available in the literature in the context of developing countries, primarily due to limited data availability (*11*). In a notable study, Fujiwara et al. (*12*) reported, based on a stated preference survey of mode choice in Yangon, Burma, that users' sensitivity to travel time and cost varies across different income groups.

Another study (*13*) compared three causal studies to investigate the relationship between mode choice and complex trip-chaining patterns. Miller et al. (*14*) studied household-level, tour-based mode choice using a microsimulation framework. This study did not take into account the consumption component and also used a combinatorial method of accounting for multiple modes being chosen, which makes it computationally burdensome.

It can be inferred that there is a need for mode choice models at the household level, which also account for multiple discreteness in choice through an analytically tractable modeling framework. Also, more studies need to be done in developing countries with comprehensive, disaggregate data.

Travel Expenditure Analysis

In contrast to the numerous studies on travel time use and allocation research, relatively fewer studies have focused on modeling travel money expenditure, mainly because of data requirements. Zahavi's work (*15*) on the unified model of traffic dealt with the regularity in travel money and time expenditure as well as the effect of income level, network speeds, and car ownership on travel money expenditures. Another notable study (*16*) found that travel money was stable in time and space and thus could be regarded as a travel money budget. Travel and household survey data from various surveys were collected and analyzed current maintenance and running costs for personal vehicles and other out-of-pocket travel costs (*17*). Tanner (*18*) used the seventh-day data of the 1975–1976 National Travel Survey to examine travel time and money expenditures by household income, density, and mode. Studies have used a utility-maximizing simultaneous equations approach (*19*) to model households' activity participation under fixed time and cost budget constraints. More recently, Thakuriah and Liao (*20*) used the Consumer Expenditure Survey data to explore vehicle ownership expenditures, controlling for socioeconomic, demographic, life-cycle, and other household factors.

There is a significant need for more behavioral models for travel money expenditure analysis—not just on personal vehicles but on other modes as well. Introduction of a budget constraint in the model for travel cost at a household level would also contribute to a more realistic analysis of travel cost expenditure.

Interested readers are referred to Bhat (*1*) for a detailed review of multiple discrete choice models and discrete–continuous models in the literature.

DATA DESCRIPTION

This study uses disaggregate data from the Chennai Household Travel Survey conducted between December 2004 and April 2005. The city of Chennai has a population of around 7 million and the greater metropolitan region covers nearly 1,167 km^2. The study sample was selected at random from 12 zones in Chennai considered to be representative of the city at large (*21*). Data were obtained in face-to-face interviews from the households. The households represent 0.5% to 0.7% random samples from the selected zones. The survey was specifically designed with the aim of understanding the changes in sociodemographic characteristics, mode choice, vehicle ownership, land use and activity patterns, and mobility-related variables and their influence on changes in travel patterns in Chennai over the last 5 years.

The sample values are consistent with population values with regard to average household size (4.51 people), average age of workers (38 years), and percentage of males in the workforce (78%) (*22*). The average income in the sample is also similar to the values of the population [estimated to be Rs. 16,786 per month (Rs. 1 = $0.02 in 2002 U.S. dollars), by projecting 2001–2002 values reported for Chennai by National Council of Applied Economic Research Report (*23*) with an inflation rate of 5%].

Figure 1 shows the distribution of the total number of modes chosen by a household (work and nonwork trips). The average values of other relevant variables are presented in Table 1. From Figure 1, it is clear that, at the household level, mode choice is a multiple discrete outcome rather than a single discrete decision. Only about 36% of households chose just one motorized mode. Nearly 40% of households chose more than one motorized mode, thus providing evidence for multiple-mode choice (and usage) at the household level.

In Table 1, in the section on household-level mode choice, an important observation is that among households that collectively use only one motorized mode, a significant number (85.61%) own and use a personal vehicle. Also, with an increasing number of modes chosen by a household (i.e., multiple-mode choice), mode shares of public transit and IPT dramatically increase, whereas personal vehicle mode share remains almost constant at any level of multiple-mode choice (85%). This result shows that multiple-mode choice is most likely to lead to balanced mode usage rather than just personal vehicle usage.

Other significant findings from the preliminary data analysis specific to developing countries include (*a*) a significant presence of nonworkers at home, with nearly 87.5% of households having at least one nonworker and nearly 45% having two or more nonworkers at home; (*b*) much less driving knowledge among female workers (16.28%) than among male workers (83.75%); (*c*) significantly high use of mobile phones (88%); (*d*) less train access than bus access, possibly due to a lack of proper feeder channels to railway stations; and (*e*) higher two-wheeler ownership rate (51%) and lower four-wheeler ownership rate (20.06%) among households in the neighborhood.

These findings, much different from those in developed countries, reinforce the motivation to analyze mode choice mode usage in developing countries. Figure 2 shows the distribution of total monthly travel expenditure on all available modes. About 39% of households spent less than Rs. 500, whereas only 13% of households spent more than Rs. 3,000 per month. Table 1 also shows that the average expenditure on personal vehicles far exceeds that for other modes.

MODELING METHODOLOGY

Household-Level Mode Choice

Every individual making a mode choice decision is a part of a household. Because of the household's fixed-cost budget for travel expenses, various members of the household may try to modify their mode choice decisions to minimize travel expenses subject to this budget constraint. Thus, the household is the basic decision-making unit where group decision making can be explicitly observed. On the basis of the intuitiveness of how the potential interdependence between individual mode choices at the household level (as in the above

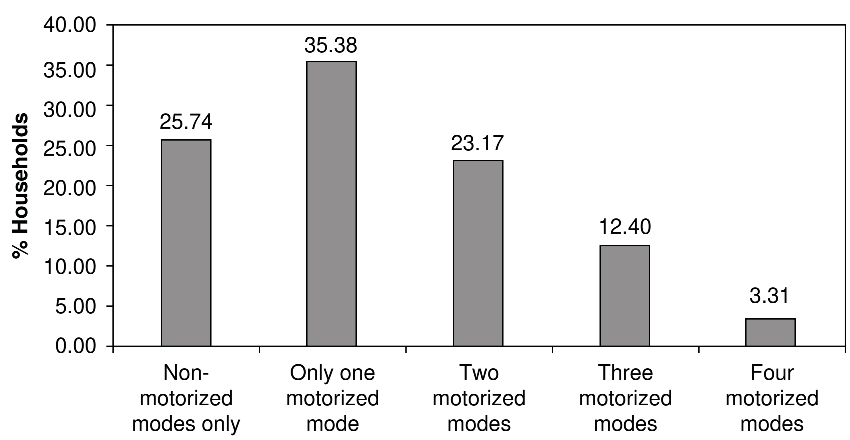

FIGURE 1 Distribution of total number of motorized modes chosen by household.

TABLE 1 Descriptive Statistics of Chennai Household Travel Survey Data

Sample size	2,086 households			
Household-level mode choice	Total number of motorized modes chosen			
	1	2	3	4
% households using bus	3.91	36.67	87.64	100
% households using train	0.69	7.67	36.65	100
% households using personal vehicle	85.61	83.79	86.85	100
% households using IPT	9.77	71.85	88.84	100
% household income spent on travel	14.8% (Stdev = 17.7%)			
Travel cost expenditure				
Mean monthly household expenditure on travel by				
Bus (regular + season tickets)	Rs. 378.08 (Stdev = Rs.451.5)			
Train (regular + season tickets)	Rs. 293.67 (Stdev = Rs.393.55)			
Personal vehicle (loans, maintenance, fuel, insurance etc)	Rs. 1,709.53 (Stdev = Rs.1,583.13)			
IPT and other modes (school bus, share-auto etc)	Rs. 549.78 (Stdev = Rs.662.75)			
Mean total monthly household expenditure on travel	Rs. 1,887.45			
Other descriptive statistics relevant to developing countries				
Household-level attributes				
Household size (mean)	4.3			
Household income (mean)	Rs.15,195.1			
Average vehicle ownership per household	1.28			
Average number of 2 wheelers per household	1.05			
Average number of 4 wheelers per household	0.23			
Households having mobile phone(s)	88.24%			
Person-level attributes				
Average number of workers per household	1.50			
Average number of female workers	0.30			
Average number of male workers	1.20			
Average age of workers	37.1 years			
Average driving experience	8.8 years			
Driving knowledge among workers				
Male	83.75%			
Female	16.28%			
Nonworkers at home				
Households having 0 nonworkers	12.5%			
Households having 1 nonworker only	43.18%			
Households having 2 nonworkers only	26.87%			
Households having 3 or more nonworkers	17.40%			
Average number of children accompanied by adults in their school/college trips	0.23			
Average number of children below 5 yrs of age per household	0.20			
Average number of children between 5 yrs and 18 yrs of age per household	0.71			
Peer and location effects				
Average number of households owning two wheelers per 10 households in the neighborhood	5.10			
Average number of households owning four wheelers per 10 households in the neighborhood	2.06			
Households living in urban areas	40.4%			
Households living in peri-urban areas	28.6%			
Households living in suburban areas	31%			
Accessibility to public transit				
Households where bus stop is within 500 m from home	84.78%			
Households where railway station is within 1 km from home	36.15%			
Workers who have access to bus stand within 500 m from workplace	76.04%			
Workers who have access to railway station within 1 km from workplace	40%			

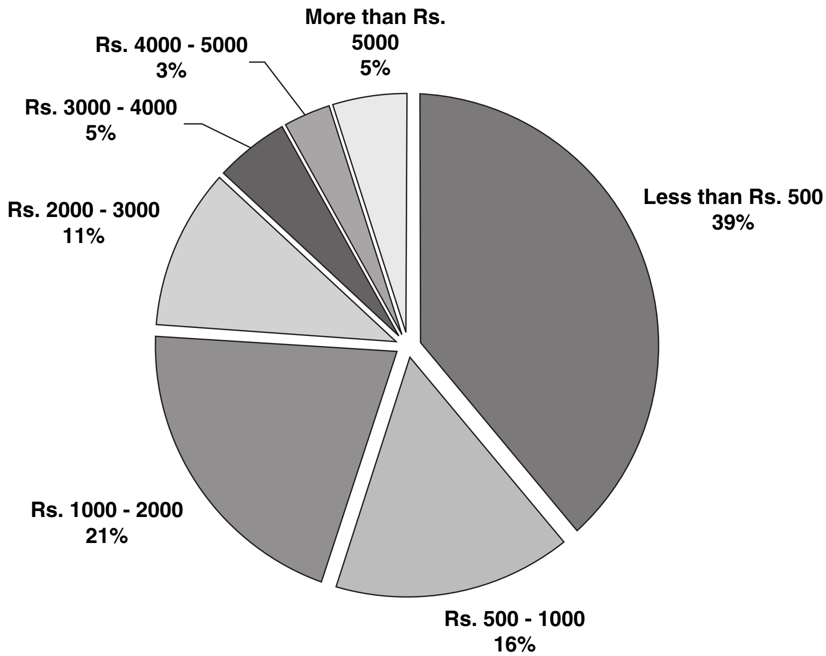

FIGURE 2 Distribution of total monthly travel expenditure of household.

observation) and some of the descriptive statistics (e.g., Figure 1), it is hypothesized that mode choice is a household-level decision and the following MDCEV framework is proposed to implement this hypothesis.

Multiple Discrete–Continuous Extreme Value Model

Problem Features

The observed mode choice consists of a discrete and a continuous component. The discrete component relates to the modes selected by the household, whereas the continuous component relates to the intensity of usage of the selected modes (modeled here through modal expenditures). MDCEV, being a discrete–continuous model, enables the seamless integration of the discrete and continuous components, besides capturing multiple discreteness.

Simultaneous equations, ordinary least squares, and Tobit models can model the continuous components but are not integrated with the discrete components. The other shortcoming of these models is that they are mainly statistical and lack a coherent behavioral framework underlying the observed decisions. These models yielded counterintuitive results and poor goodness-of-fit (not reported here because of lack of space). On closer examination, these results were found because the expenditure variable did not follow a normal distribution and the ordinary least squares was unable to model the truncation at zero for modes not chosen by the household.

Behavioral Framework

Let there be I different travel modes that a household can potentially use. Let e_k be the monthly travel cost expenditure on mode k ($k = 1, 2, \ldots, I$) and let B denote the total travel budget available to a household. The household subscript h is suppressed for notational convenience below.

A constrained utility maximization framework is used to model the selection of modes at the household level as well as the associated travel expenditures on each mode. Accordingly, it is assumed that the household seeks to maximize its total utility by consuming various quantities corresponding to the different modes, subject to the budget constraint $\sum_k e_k \leq B$. This optimal consumption vector that maximizes the household utility is denoted by $e^* = \{e_1^*, \ldots, e_k^*\}$.

Model Specification

It is assumed that the household utility U is a function of the consumption vector $e = \{e_1, \ldots, e_k\}$ and can be expressed as the sum of the modal utilities U_k. The utility of mode k is assumed to be made up of two components: a baseline component (ψ_k) and a component (π_k) that depends on the intensity of consumption (e_k). A multiplicative error term of the form $\exp(\epsilon_k)$ is assumed for mode k (random utility), where the errors ϵ_k represent unobserved terms that affect the utility. These errors ϵ_k are assumed to follow an independent and identically distributed (iid) and standard Gumbel distribution. The form and distribution of ϵ_k ensures the utility function is valid and an analytical closed-form expression for the likelihood (*1*).

Accordingly, the modal utility U_k is assumed to take the form $U_k = \psi_k \pi_k(e_k) \exp(\epsilon_k)$. The choice and specification of the baseline and intensity-dependent components are predicated on the following assumptions:

1. A greater intensity of use for a given mode represents a greater strength of preference for a given mode. The modal utility U_k is an increasing function of e_k, consistent with the microeconomic framework.

2. The additional increment of consumption may provide a smaller increase in utility of that mode at a higher level of consumption than

at a lower level of consumption (i.e., $dU_k/de_k \leq 0$). This property is particularly important, as it allows for a trade-off between consumption levels of alternative modes, resulting in the selection of multiple modes (with equal marginal utilities as shown later). Bhat (*1*) referred to this property as satiation with an alternative. However, in the context of household mode choice, other sources are identified—distinct from satiation—that can also lead to diminishing marginal returns (see the section on effects on diminishing marginal returns).

To reflect these assumptions, the following specification is used for the deterministic baseline and intensity-dependent utility components.

Baseline deterministic utility specification. Baseline utility of mode k (when consumption $x_k = 0$):

$$\psi_k = \exp(\beta_k z_k)$$

where z_k is a vector of parameters characterizing the household and mode k (sociodemographic variables, accessibility of the mode, travel time, land use variables, and relevant interaction variables) that affect the baseline utility for mode k, and β_k is a vector of parameters influencing baseline utility.

Intensity-dependent utility π_k specification. It is assumed that the intensity-dependent utility component

$$\pi_k(e_k) = \left\{ \frac{(1+e_k)^{\alpha_k} - 1}{\alpha_k} \right\}$$

where the term α_k influences the rate of diminishing marginal utility from using a particular mode k. To see this, note that

$$\frac{dU_k}{de_k} = \psi_k \pi_k'(e_k)\exp(\epsilon_k) = \psi_k (1+e_k)^{\alpha_{k-1}} \exp(\epsilon_k)$$

Thus, if $\alpha_k = 1$, the marginal utility is constant. If $\alpha_k < 1$, the marginal utility decreases, and $\alpha_k > 1$ indicates an increasing marginal utility function.

To reflect the fact that the marginal utility rate is a function of household and modal characteristics, this term is parameterized as follows:

$$\alpha_k = \frac{1}{\left(1 + e^{-\theta_k Y_k}\right)}$$

where Y_k is a vector of household and modal characteristics influencing the marginal utility for the kth alternative, and θ_k is a corresponding vector of parameters. This parameterization implies that $0 < \alpha_k \leq 1$, thus ensuring that Assumptions 1 and 2 are satisfied. A negative α value would imply a decreasing utility function, and a value > 1 would imply an increasing marginal utility.

Model Estimation

An outline of the estimation procedure is presented here and closely follows the MDCEV model estimation procedure by Bhat (*1*) and may be skipped by readers familiar with the procedure. The only difference is that the γ parameter of Bhat (*1*) is set to 1 to avoid identification problems and only the α_k terms are estimated in this study.

The utility maximization problem above can be converted into an equivalent Lagrangian form by including the constraint as a part of the objective function as shown below:

$$\text{maximize } L(U, B) = \sum_k U_k - \lambda\left[\sum_k e_k - B\right]$$

The optimal solution e^* can be obtained by solving first-order Kuhn–Tucker conditions below:

$$\Psi_k\left(1+e_k^*\right)^{\alpha_{k-1}} - \lambda = 0 \qquad \text{if } e_k^* > 0 \qquad k = 1, 2, \ldots, I$$

$$\Psi_k\left(1+e_k^*\right)^{\alpha_{k-1}} - \lambda < 0 \qquad \text{if } e_k^* = 0 \qquad k = 1, 2, \ldots, I$$

These conditions imply that the marginal utilities at optimality are equal for all used modes and larger than the marginal utility of any unused mode.

Setting $\lambda = [\exp(\beta' x_1 + \epsilon_1)]\alpha_1(e_1^* + 1)^{\alpha_1 - 1}$ = marginal utility of the first chosen alternative.

$$\log\lambda = \beta' x_j + \ln\alpha_j + (\alpha_j - 1)\ln\left(e_j^* + 1\right) + \epsilon_j \tag{1}$$

for all modes j that are selected.

The corresponding deterministic component of log λ is denoted as follows:

$$V_j = \beta' x_j + \ln\alpha_j + (\alpha_j - 1)\ln\left(e_j^* + 1\right)$$

for ($j = 1, 2, 3, \ldots, I$).

Substituting for λ from above into Equation 1 for the other modes ($k = 2, \ldots, I$), the Kuhn–Tucker conditions can be expressed in logarithmic form as follows:

$$V_j + \epsilon_j = V_1 + \epsilon_1 \qquad \text{if } e_j^* > 0 (j = 2, 3, \ldots, I)$$

$$V_j + \epsilon_j < V_1 + \epsilon_1 \qquad \text{if } e_j^* = 0 (j = 2, 3, \ldots, I) \tag{2}$$

The likelihood consists of two types of terms: the first corresponds to the modes that are chosen (with positive consumption and expenditures) and those that are not chosen (consumption = 0). The above equation shows that the corresponding likelihood terms for the first case reflect the density function at the corresponding utility values (reflected as equality), and for the second case they represent a discrete choice probability relative to the chosen alternatives.

From Equation 2, it has been shown (*1*) that the probability that the individual selects M of the I modes ($M \geq 2$), given ϵ_1, is

$$P\left(t_2^*, t_3^*, \ldots, t_M^*, 0, 0, \ldots, 0\right)\big|\epsilon_1 = \left\{\left(\prod_{i=2}^{M} g\left(V_1 - V_i + \epsilon_1\right)\right)|J|\right\} \times \left\{\prod_{s=M+1}^{K} G\left(V_1 - V_s + \epsilon_1\right)\right\} \tag{3}$$

where

g = standard extreme value density function,
G = standard extreme value cumulative distribution function, and
J = Jacobian function.

Refer to Bhat (*1*) for a detailed derivation of this result and form of the Jacobian.

Under the assumption that the error terms follow an iid Gumbel distribution, the likelihood of observing the given consumption vector without loss of generality assuming that the first M modes of I modes are selected with consumption quantities ($e_1^*, e_2^*, e_3^*, \ldots, e_M^*, 0, 0, \ldots, 0$) can be shown to be

$$
\begin{aligned}
P\left(e_2^*, e_3^*, \ldots, e_M^*, 0, 0, \ldots, 0\right) &= \int_{\epsilon_1} P\left(e_2^*, e_3^*, \ldots, e_M^*, 0, 0, \ldots, 0 \mid \epsilon_1\right) g(\epsilon_1)\, d\epsilon_1 \\
&= \left[\prod_{k=1}^{M} c_k\right]\left[\sum_{k=1}^{M} \frac{1}{c_k}\right]\left[\prod_{i=2}^{M} e^{-(V_1 - V_i)}\right] \\
&\quad \int_{\epsilon_1=-\infty}^{+\infty} \left\{ \left(e^{-\epsilon_1}\right)^{M-1} \cdot e^{-\sum_{k=1}^{I}\left[e^{-(V_1 - V_j + \epsilon_1)}\right]} \cdot e^{-\epsilon_1} \right\} d\epsilon_1 \\
&= \left[\prod_{k=1}^{M} c_k\right]\left[\sum_{k=1}^{M} \frac{1}{c_k}\right]\left[\frac{\prod_{k=1}^{M} e^{V_k}}{\left(\sum_{j=1}^{I} e^{V_j}\right)^{M}}\right](M-1)!
\end{aligned}
$$

where

$$c_k = \left(\frac{1-\alpha_k}{e_k^* + 1}\right)$$

The log of this likelihood is maximized corresponding to the observed consumption vector to obtain estimates of the model parameters α_k and θ_k. The maximum likelihood estimation technique is used, given its desirable asymptotic properties: unbiasedness, consistency, efficiency, normality, and model results are described in the following sections.

The primary advantages of the proposed MDCEV model for the household-level analysis of mode choice include its ability to

1. Capture multiple discreteness;
2. Provide a logical, computationally efficient, and consistent representation of the linkage between discrete and continuous components of choice (e.g., if a given mode is not selected by a household, the corresponding mode share and usage levels will be zero);
3. Account for diminishing marginal utility in choice with increasing consumption; and
4. Model intermodal linkages, budget constraints, and intrahousehold interactions that affect mode choice.

The conventional single discrete choice model can be obtained as a special case of the multiple discrete model. Further, the single discrete choice model (e.g., multinomial logit) assumes that the utility is independent of the magnitude of consumption. These assumptions can be statistically tested by examining whether the terms $\alpha_k = 1$ for all modes.

EMPIRICAL RESULTS

Mode Choice Component

The mode choice component is represented by the term $\beta_j' x_j$ in the deterministic utility V: $V_j = \beta' x_j + \ln \alpha_j + (\alpha_j - 1)\ln(e_j^* + 1)$ for ($j = 1, 2, 3, \ldots, I$) [see MDCEV probability expression in the previous section]. Table 2 presents the MDCEV model results of the final specification, along with the t-statistics of the estimated parameters. The results from the final specification are explained as follows.

Baseline Preference Constants

Personal vehicle is taken as the baseline alternative. The baseline preference constants for the other three modes indicate that, relative to a personal vehicle, households have less preference for public transportation. Intrinsic preference for IPT modes is found to be greater than that for public transportation but less than for a personal vehicle, after controlling for other variables. This finding is consistent with the average attitudinal behavior of individuals toward travel modes and may reflect intrinsic preference toward comfort and convenience and constraints associated with alternative modes.

Household Structure

The baseline segment used in household structure segments is the single male worker belonging to an extended family segment. The household structure variables are household-level attributes used to explain the interperson interactions.

Extended Family Households Extended family households with a single female worker showed less preference toward a personal vehicle than toward bus and IPT. A possible reason for this finding is the lack of driving knowledge among female workers, as indicated in the descriptive statistics (Table 1). Extended family households with only multiple male workers, on the other hand, showed a greater inclination toward choosing bus and personal vehicle. Households with multiple male workers and no female workers were found to belong to the lower income segment (<Rs. 8,000 per month), and the male workers usually undertake a larger share of out-of-home maintenance activities. The need for increased mobility is evident in their preference toward a personal vehicle. Males' lower sensitivity to in-vehicle crowding along with the cost efficiency of public transit contribute to their preference for bus, subject to vehicle availability constraints.

Extended family households with more male workers than female workers showed a strong positive preference for a personal vehicle and bus but also showed the least preference toward the IPT modes (auto-rickshaws). This finding could be attributed to increased ride-sharing and greater driving knowledge in the case of excess male workers. On the other hand, an extended family with excess female workers (i.e., more than male workers) showed the greatest preference toward IPT modes, compared with public transport and personal vehicles.

Nuclear Family Among nuclear families and couples, the single-male-worker category had the largest number of observations. Such households show a greater preference for a personal vehicle, primarily due to greater driving knowledge among male workers, child-care-related mobility needs, and the greater comfort level of personal vehicles. Single-female-worker-only nuclear households showed a reduced preference toward bus and personal vehicle but higher IPT preference (as inferred from additional specifications) mainly due to a lack of driving knowledge, greater privacy needs among female workers, and an increased proportion of expenditures for child care.

TABLE 2 MDCEV Model Estimation Results

Parameter Description	Bus	Train	Personal Vehicle	IPT
Mode Choice Component				
Constant	−1.45 (−26.01)	−3.03 (−33.85)	Baseline	−0.35 (−7.01)
Family structure				
Extended family single male worker is baseline segment				
Extended family (3 or more adults with or without children below 18 years)				
Single female worker only	*0.51 (1.33)*	—	—	*0.51 (1.33)*
Multiple male workers only	0.40 (2.83)	—	0.40 (2.83)	—
Male workers > female workers	0.22 (2.11)	—	0.22 (2.11)	−0.87 (−2.70)
Female workers ≥ male workers	—	—	—	0.13 (1.77)
Nuclear family (couple with children)				
Single male worker only	—	—	0.21 (1.93)	—
Single female worker only	−1.18 (−1.73)	—	−1.18 (−1.73)	—
Other developing country-specific factors				
Peer group effects				
Two-wheeler ownership in the neighborhood (#HH out of 10 HH in the immediate neighborhood that own a two-wheeler)	0.30 (40.28)	0.30 (40.28)	—	0.15 (20.30)
Four-wheeler ownership in the neighborhood (#HH out of 10 HH in the immediate neighborhood that own a four-wheeler)	—	—	0.25 (19.81)	0.32 (22.16)
Nonworker effects and other resource-based coordination effects				
Number of workers returning home for lunch.	0.21 (2.46)	—	0.50 (7.64)	—
Suburban household has train access as well as own vehicles and nonworkers are present.	—	1.43 (6.50)	0.78 (5.31)	—
Suburban household has own vehicles and nonworkers are present, but there is no train station within a 1-km radius.	—	0.22 (2.12)	1.06 (8.62)	—
Workers in HH make no intermediate stops on the way from/to workplace. Nonworkers present. Mixed land use in household's neighborhood.	0.31 (4.97)	0.31 (4.97)	0.26 (4.96)	—
Workers in HH make no intermediate stops on the way from/to workplace. Mixed land use, but HH has no nonworkers.	*0.05 (1.25)*	—	0.43 (3.02)	—
Mode Usage Component				
Constant	1.45 (33.34)	1.66 (17.48)	9.89 (73.64)	1.49 (46.20)
State dependence effects (inertia effects)				
Choice of bus 5 years back	1.03 (3.13)	—	6.61 (2.34)	−0.74 (−3.45)
Choice of train 5 years back	—	1.03 (3.13)	—	—
Choice of personal vehicle 5 years back	−0.35 (−1.91)	−0.35 (−1.91)	—	−0.37 (−2.48)
Choice of IPT 5 years back	—	—	—	0.57 (1.46)
Inconvenience/perceived inconvenience (These are derived from user perceptions of quality and level of service in their neighborhood, collected as a ranked response)				
High congestion on roads	—	0.06 (2.30)	−3.27 (−44.62)	—
Low safety level for pedestrians	*−0.04 (−1.31)*	*−0.04 (−1.31)*	0.52 (6.19)	0.05 (2.30)

Log likelihood at zero:	−21,708.31	Number of parameters:	37
Initial log likelihood:	−12,150.49	χ^2 statistic = $2[LL_{convg} - LL_{initial}]$:	997.70
Log likelihood at convergence:	−11,651.64	Critical χ^2 value for 37 d.o.f.:	69.34

NOTE: Entries in the table marked "—" imply that they were tested in the initial specifications, but were dropped in the final specification. Estimates that are italicized are not significant at the 85% confidence level but are included in view of theoretical interest. HH = household, LL = log likelihood, d.o.f. = degrees of freedom.

Peer Group Effects The peer group effects in this study refer to the influence of two-wheeler and four-wheeler ownership in the immediate neighborhood of the household. Households living in neighborhoods with a high rate of car ownership (>5 cars owned among 10 households in the neighborhood) were more likely to choose a personal vehicle (especially four-wheelers) and IPT. This finding suggests that either residential choice may be self-selected based on vehicle ownership and social status or the household-level mode choice decisions are influenced by the decisions of other individuals present in the neighborhood. In contrast, respondents living in neighborhoods with higher two-wheeler ownership rates (>7 two-wheelers owned among 10 households in the neighborhood) are more likely to use public transportation modes. These results are consistent with other studies in developing countries, which found that households with only two-wheelers are more likely to consider switching to public transport than households that have a car (*24*).

Other Effects Specific to Developing Countries

Time-Related Constraints It was found that households where workers return home for lunch show a greater preference (nearly twice as large) for a personal vehicle (coefficient = +0.50) relative to a bus (coefficient = +0.21). Returning home for lunch involves greater coordination between workers and nonworkers (if any, usually the homemaker is at home). Because workers must come home, have lunch, and leave in a restricted time window (usually 60–90 min), personal vehicles are preferred to public transport because of the greater mobility provided by personal vehicles.

Nonworker Vehicle Usage Suburban households with nonworkers but without access to a train showed greater preference for a personal vehicle (coefficient = +1.06) and much less preference for a train (coefficient = 0.22). This finding is primarily due to use of a personal vehicle by workers for long-distance work trips from suburban locations. The resulting lack of vehicle availability at home is likely to be reflected in the lesser delegation of local out-of-home maintenance trips (bank, post office, etc.) to the nonworker. In contrast, when there is access to a train, the preference toward a train was intuitively much higher (coefficient = +1.43), but the preference for a personal vehicle was still positive (although it decreased significantly; coefficient = +0.78).

The latter situation, besides being a clear indication of multiple-mode usage, also shows greater delegation of out-of-home maintenance trips to nonworkers. Because the worker is most likely to use a train to commute, the personal vehicle is likely to be left at home and is available to nonworkers. The significant decrease in the personal vehicle's coefficient is attributable to the nonworker's personal vehicle use for local, nonwork trips rather than for mandatory, long-distance work commutes from suburban locations. This finding provides evidence of complex activity substitutions and vehicle allocation across household members that influence mode choice decisions, which cannot be captured easily through standard mode choice models used at the individual level of disaggregation. The two variables used above are interaction variables between different household-level attributes (household location, vehicle ownership, and access to train) and individual proxies for explaining household interaction.

Activity Delegation to Nonworkers Mixed land use is widely prevalent in the city of Chennai, with a high density of activity centers in residential neighborhoods and with the potential for increasing nonmotorized and public transport usage. Results from this study indicate that effects of land use on mode choice are also subject to intrahousehold interactions. It was found that when nonworkers are present, households in mixed land use areas and where workers do not make any intermediate stops in their work trips show greater preference for public transport (coefficient = +0.31) and less preference for a personal vehicle (coefficient = +0.26). But the absence of nonworkers in these households significantly increases their preference for a personal vehicle (coefficient = +0.43) and significantly decreases their preference for public transportation (coefficient = +0.05) despite the mixed land use.

Because workers do not make intermediate stops, the nonworkers make local out-of-home maintenance trips and also take care of in-home activities in the workers' absence. The absence of nonworkers at home shifts this responsibility to workers. However, as workers do not make intermediate stops on their work trips, these respondents have to make separate trips for this purpose. This increase in the workers' mobility needs is better facilitated by a personal vehicle than by public transport, which is reflected in the mode choice as shown above. This finding highlights the moderating role of worker–nonworker interaction at the household level on the impact of mixed land use on transit ridership. The above two variables are interaction variables among different household-level attributes (mixed land use in the neighborhood, vehicle ownership) and individual proxies for explaining household interaction.

Mode Usage Component

Constants

The values of constants indicate that the intrinsic tendency to use a personal vehicle (i.e., the marginal utility) is much higher than that of other modes. The α parameter value at zero coefficients—that is, $1/[1 + \exp(-\delta_j)]$, which lies between 0 and 1—is 0.99 for a personal vehicle. The α parameter values at zero coefficients for bus, train, and IPT are 0.81, 0.84, and 0.82, respectively. As a higher value of α implies a greater marginal utility value, the initial marginal utility of a personal vehicle is very high compared with that of other modes, implying that households are more likely to spend more on personal vehicles than on any other mode. This finding may be attributed to the greater willingness to spend more per unit distance on a personal vehicle than on other modes given its greater comfort, convenience, and so forth.

Effects on Diminishing Marginal Returns

State-Dependence Effects Households that previously (5 years ago) chose bus and train are more likely to retain those modes now (coefficient for bus and train = +1.03). In other words, these households have a greater marginal utility for the corresponding public transit mode with which they are familiar. On the other hand, households that previously chose public transit also show a greater tendency to spend on a personal vehicle, which is a sign of increasing preference toward personal vehicles even among no-vehicle households. However, the coefficient in the variable in a personal vehicle's utility is rather large (coefficient = +6.61). The reason for the relatively large magnitude for this variable is unclear and remains to be understood through further improvements in specifications.

Households that previously chose a personal vehicle show significantly less marginal utility for public transportation and IPT, indicating captivity to personal vehicles. One possible reason could be that having already invested in a personal vehicle, they are justified to use it rather than switching to public transportation. A similar trend was observed in IPT state dependence on IPT usage now (coefficient = +0.57). Although similar trends of declining public transport mode shares (probabilities) were noted in prior studies (*25*), the above finding is different in that the inertia toward switching to public transit modes also manifests itself in the form of decreasing intensity of mode use. Thus, there is a need to take measures and evolve transit policies that reduce this inertia as well as the tendency for reduced consumption.

Inconvenience and Perceived Inconvenience One advantage of the MDCEV model is that it can capture the diminishing marginal returns resulting from increasing levels of consumption of a given mode. The α term in the few MDCEV models in the literature have mainly aimed to capture the satiation effect. In contrast, perceived inconvenience is different from satiation in the sense that whereas satiation is contingent on usage, perceived inconvenience does not have prior usage of an alternative as a prerequisite for any change in marginal utility. Two important policy-sensitive quality-of-service attributes are included in the final specification in this category.

High congestion on roads leads to a greater tendency to use a train (coefficient = +0.06) and significantly less usage tendency (lesser marginal utility) for a personal vehicle (coefficient = −3.27) and other road-bound modes. This finding could be important in proposing policy measures to improve the mode share of train, which can contribute to congestion mitigation and reduced energy consumption and emissions on the road network.

A low pedestrian-safety level was found to decrease the usage tendency (less marginal utility) for bus and train (coefficient = –0.04) and significantly increase the tendency to use personal vehicles (coefficient = +0.52) and IPT (coefficient = +0.05). This finding is possibly due to the following reason. Public transport users significantly use nonmotorized modes as part of their journey. It is the nonmotorized leg of the journey that makes them sensitive to pedestrian-safety levels (walking or cycling to the bus stand or railway station). Personal vehicles and IPT, on the other hand, involve significantly less nonmotorized vehicle use and are safer modes to use when pedestrian-safely levels are low. This finding is also important in planning policy measures to improve pedestrian-safety levels, thereby improving public transit mode share.

Goodness-of-Fit Measures

The log likelihood for the equally likely model is −21,708.61. For the constants-only MDCEV model, it is −12,150.49, whereas the log likelihood at convergence is −11,651.64. The likelihood ratio test for testing the presence of the baseline utility variables as well as the variables affecting the diminishing marginal returns is 997.70, which is significantly greater than the critical χ^2 value for 37 degrees of freedom. Thus, the model passes the likelihood-ratio test and has a reasonably good likelihood ratio index ($\rho^2 = 0.46$).

Assumptions and Exceptions

Because of limitations in sample size, nature of the data, and modeling assumptions in this study, the insights here need to be confirmed with empirical data from similar contexts. Generalizing this work by relaxing the iid error structure, possibly accounting for correlations among mode combinations, offers scope for improvement. The MDCEV model proposed here captures only the modal use and expenditure decisions among motorized modes and not nonmotorized modes such as walking (as no operating cost is incurred). Also, because travel cost was included as a dependent variable, explicit introduction of travel time is difficult because of possible correlations between time and cost. However, specific quality-of-service attributes were included in the current model (see the section on effects on diminishing marginal returns). Capturing level-of-service variables in a more explicit manner as well as integrating modal intensity use decisions with regard to walk and bicycle remain an important direction for further investigations.

SUMMARY AND CONCLUSIONS

This study analyzes mode choice decisions at the household level instead of at the individual level, given the strong interpersonal linkages and constraints within a household that influence these decisions, in the context of a developing country. Through relevant descriptive statistics, it was found that, at the household level, mode choice is a multiple discrete (i.e., multiple modes may be chosen by a single decision-making unit) outcome rather than a single discrete outcome. The MDCEV model was used to model choice and consumption simultaneously, as a single, coherent, and mutually consistent model.

Several unique features in developing countries relevant to household-level mode choice were analyzed and found to be significant in affecting household-level mode choice, including mixed land use, extended-family system, nonworker availability, use of two-wheelers and IPT, and so forth. State dependence and perceived inconvenience effects are proposed to affect the diminishing marginal returns, in contrast to satiation effects noted in prior MDCEV literature.

Some of the salient empirical findings and results are summarized below:

1. As the number of modes collectively chosen at the household level increases, the percentage of households choosing public transit and IPT increases significantly, and personal vehicle choice remains unaffected (85%). This finding shows that multiple-mode choice leads to greater use of public transit than single-mode choice.
2. Extended families show a greater tendency to choose multiple modes (i.e., personal vehicle and public transportation) than nuclear families.
3. Four-wheeler ownership in the neighborhood showed a stronger preference for personal vehicle and IPT usage. On the other hand, two-wheeler ownership in the neighborhood showed a positive preference for public transport and IPT.
4. Increased congestion on roads increases a household's usage tendency (i.e., expenditure) toward train and significantly decreases the usage tendency for personal vehicles, among other modes.
5. Poor pedestrian-safety levels reduced the households' marginal utilities (i.e., tendency to use and spend) for public transport and showed significantly increased usage tendencies for personal vehicle and IPT.
6. State dependence (inertia in mode switching) is evident among all mode users, but households that previously chose bus over a period of time showed a higher tendency to spend on a personal vehicle than on a bus.

The findings from this study can be used to support policy evaluation and decision making along the following lines. Multiple-mode usage leads to increased public transit mode share and therefore more balanced usage of modes than single-mode choice (mostly a personal vehicle). Factors that were significant determinants of multiple-mode usage in developing countries include joint family structure, mixed land use, suburban location of households, and access to public transit.

Congestion mitigation measures may be instituted by encouraging train use through better feeder routes to railway stations, as households show a positive tendency to use train and a strong disinclination for a personal vehicle and other modes when road congestion levels are high. Similarly, households that previously chose public transit show a tendency to switch to personal vehicles and therefore would increase congestion on roads. Suitable policy measures should be introduced to retain such users on public transit modes. Also four-wheeler-owning households show a disinclination toward public transit modes and are more likely to use a personal vehicle and IPT, which can contribute to a further increase in congestion.

This study also provides evidence of strong intermodal linkages in mode choice in developing countries. The choice of public transport is influenced by congestion on roadways and accessibility to trains. In addition, poor perception of pedestrian safety can lead to a reduction in intensity of public transit usage. Thus, the provision of more pedestrian-friendly bus bays and safer pedestrian walks could potentially reduce the usage of personal vehicles and IPT, thereby promoting greater intensity of nonmotorized usage and greater public transit preference. These findings highlight the need for integrating nonmotorized and transit planning closely with land use patterns to achieve desirable transportation system outcomes.

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REFERENCES

1. Bhat, C. R. A Multiple Discrete–Continuous Extreme Value Model: Formulation and Application to Discretionary Time-Use Decisions. *Transportation Research B,* Vol. 39, No. 8, 2005, pp. 679–707.
2. Ben-Akiva, M., and S. R. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand.* MIT Press, Cambridge, Mass., 1985.
3. Ortuzar, J. D., and L. G. Willumsen. *Modeling Transport.* John Wiley & Sons, New York, 2001.
4. Bhat, C. R. Incorporating Observed and Unobserved Heterogeneity in Urban Work Mode Choice Modeling. *Transportation Science,* Vol. 34, No. 2, 2000, pp. 228–238.
5. Anable, J., and B. Gatersleben. All Work and No Play? The Role of Instrumental and Affective Factors in Work and Leisure Journeys by Different Travel Modes. *Transportation Research A,* Vol. 39, 2005, pp. 163–181.
6. Koppelman, F. S., and P. K. Lyon. Attitudinal Analysis of Work/School Travel. *Transportation Science,* Vol. 15, 1981, pp. 233–254.
7. Cervero, R. Built Environments and Mode Choice: Toward a Normative Framework. *Transportation Research D,* Vol. 7, 2002, pp. 265–284.
8. Munizaga, M. A., and R. Alzarez-Daziano. Testing Mixed Logit and Probit Models by Simulation. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1921,* Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 53–62.
9. Hensher, D. A., and W. G. Greene. The Mixed Logit Model: The State of Practice. *Transportation,* Vol. 30, No. 2, 2003, pp. 133–176.
10. Pinjari, A. R., and C. R. Bhat. *The Impact of Accommodating Nonlinear Response to Level of Service Variables on Unobserved Heterogeneity: A Case Study in the Context of Travel Mode Choice Models.* International Association for Travel Behavior Research Conference, Kyoto, Japan, 2006.
11. Dissanayake, D., and T. Morikawa. Household Travel Behavior in Developing Countries: Nested Logit Model of Vehicle Ownership, Mode Choice 1, and Trip Chaining. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1805,* Transportation Research Board of the National Academies, Washington, D.C., 2002, pp. 45–52.
12. Fujiwara, A., J. Zhang, and S. Thein. Using Stated Preference Approach to Estimate Mode Choice Behavior Under Changes in Travel and Socioeconomic Environments in Myanmar. *Proc., 2nd International Conference on Civil and Environmental Engineering,* Hiroshima, Japan, 2003.
13. Ye, X., R. M. Pendyala, and G. Gottardi. An Exploration of the Relationship Between Mode Choice and Complexity of Trip Chaining Patterns. *Transportation Research B,* Vol. 41, No. 1, 2007, pp. 96–113.
14. Miller, E. J., M. J. Roorda, and J. A. Carrasco. A Tour-Based Model of Travel Mode Choice. *Transportation,* Vol. 32, No. 4, 2005, pp. 399–422.
15. Zahavi, Y. *The 'UMOT' Project.* Report prepared for the U.S. Department of Transportation and the Ministry of Transport of Federal Republic of Germany, 1979.
16. Zahavi, Y., and A. Talvitie. Regularities in Travel Time and Money Expenditures. In *Transportation Research Record 750,* TRB, National Research Council, Washington, D.C., 1980, pp. 13–19.
17. Gunn, H. F. Travel Budgets—A Review of Evidence and Modelling Implications. *Transportation Research A,* Vol. 15, 1981, pp. 7–24.
18. Tanner, J. C. Expenditure of Time and Money on Travel. *Transportation Research A,* Vol. 15, No. 1, 1981, pp. 25–38.
19. Kockelman, K. M. A Model for Time and Budget-Constrained Activity Demand Analysis. *Transportation Research B,* Vol. 35, No. 3, 2001, pp. 255–269.
20. Thakuriah, P., and Y. Liao. Analysis of Variations in Vehicle Ownership Expenditures. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1926,* Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 1–9.
21. Pallavan Transport Consultancy Services. *Updating the CTTS Carried Out in 1992–95.* Publication draft final report. Tamil Nadu Urban Infrastructure Financial Services Limited, Chennai, India, 2004.
22. Census of Tamil Nadu. Directorate of Census Operations Tamil Nadu, Ministry of Home Affairs, India, 2001. www.census.tn.nic.in/pca2001.aspx. Accessed March 2007.
23. *National Council of Applied Economic Research Report.* National Council of Applied Economic Research, New Delhi, India. www.ncaer.org/Lbrry.asp. Accessed April 2006.
24. Srinivasan, K. K., P. V. L. Bhargavi, G. Ramadurai, V. Muthuram, and S. Srinivasan. Determinants of Changes in Mobility and Travel Patterns in Developing Countries: Case Study of Chennai, India. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2038,* Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 42–52.
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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