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Foreword

In the paper Travel Time Prediction and Information Availability in Commuter Behavior Dynamics, Tong et al. discuss the day-to-day dynamics of the prediction of travel time by commuters on their next trip, with particular emphasis on the effect of information availability, using an experimental approach involving commuters in a simulated commuting system. The additional information tends to reduce the perceived uncertainty associated with the system's performance; commuters combine the information with their latest experienced travel time in forming a base value for the predicted travel time on the next trip.

In their paper Nonlinear Utility in Time and Cost of Trips: Disaggregate Results from an Ordinal Methodology, McCord and Villoria discuss a new methodology to investigate the linearity of the systematic utility function over time-cost combinations. The methodology is unique in that it requires only ordinal preferences from laboratory subjects, assumes only ordinal preferences from laboratory subjects, and assumes only ordinal properties of the utility function. To illustrate the approach, the methodology is applied to a sample of 12 individuals faced with time-cost combinations of representative morning commute trips.

In his paper A Method for Estimating Long-Term Changes in Time-of-Day Travel Demand, Supernak examines the usefulness of a proposed person-category trip generation model to provide better insight into long-term changes in time-of-day travel distribution as a result of such trends as increase in female employment, increase in the average age of the population, and increase in automobile availability level. Forecast and policy implications are also discussed.

In their paper Discrete/Continuous Analysis of Commuters' Route and Departure Time Choices, Abu-Eisheh and Mannering discuss commuters' choices of routes and departure times using a discrete/continuous econometric modeling structure. The estimation results provide interesting insights into behavioral aspects motivating route and departure time choices and underscore the need for proper econometric specification in discrete/continuous model structures. The estimated models provide surprisingly good fits and show promise for application under traditional user equilibrium conditions.

Travel Time Prediction and Information Availability in Commuter Behavior Dynamics

CHEE-CHUNG TONG, HANI S. MAHMASSANI, AND GANG-LEN CHANG

The prediction of travel time by trip makers constitutes an important component of the complex daily dynamics of commuter behavior, which are of particular concern in systems evolving towards equilibrium, such as after major traffic control changes or disruptions due to major reconstruction or maintenance activities. The day-to-day dynamics of the prediction of travel time by commuters on their next trip, with particular emphasis on the effect of information availability, are investigated in this paper using an experimental approach involving commuters in a simulated commuting system. A travel time prediction model developed previously for a limited information situation provides the framework for analyzing this phenomenon, using results obtained from a second experiment where users are provided with complete information on the previous day's performance. Insights into the effect of information availability are obtained through the comparative analysis of the model's performance and estimated parameter values in the two experiments. The results suggest that additional information tends to reduce the perceived uncertainty associated with the system's performance; commuters combine this supplied information with their latest experienced travel time in forming a base value for the predicted travel time on the next trip. This base value is adjusted by a safety margin that is primarily governed by the latest experienced schedule delay, in order to protect against unacceptably late or early arrival at the workplace.

Research over the past decade has accomplished significant advances in terms of understanding and modeling travel behavior *(1)*. While much of this work has been directed towards the development of models of individual choice and decision making, little effort has addressed models of trip makers' judgment. In behavioral decision theory, judgment and choice are viewed as two integral components of the decision process *(2)*. Judgment involves the interaction between perception, learning, and information in the formation of the trip makers' anticipated values for the various attributes and performance characteristics of the travel options under consideration. Models of individual judgment are particularly important in the study of the dynamics of trip making behavior and its interaction with the performance of the transportation system. In particular, it is necessary to consider how anticipated travel times and other trip costs are formed and adjusted in response to experience with and information about the performance of the facility.

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The particular context of interest to this study is that of urban commuters in their daily trip from home to work. The dynamic aspects of this problem have received some attention over the past 5 years, primarily dealing with the time-varying flow patterns on a given day that are presumed to exist at some equilibrium point *(3–5)*. The day-to-day dynamics of this problem, and the evolution of commuters' responses to experienced travel outcomes, have more recently been the subject of theoretical and experimental investigation by the authors *(6–11)*. An essential element in this complex problem is the mechanism by which users form their estimate of the travel time that can be anticipated for a trip on a particular facility. Specifically, in a dynamically varying system, what is the relative importance of travel times experienced on preceding days in predicting the travel time to be experienced on the next trip, and how is exogenously supplied information such as from traffic reports or word-of-mouth used in this process? Answers to these questions, expressed in the form of a travel time prediction model, are necessary in the context of a dynamic modeling framework for the analysis and evaluation of congestion relief strategies in commuting corridors. Such information is also useful in examining and predicting trip pattern changes in response to major service disruptions such as major construction and repair activities.

Little previous work has addressed this particular problem. The implicit assumption made in most studies is that users have complete information about the performance of the facility in real time. When solving for a presumed equilibrium, such an assumption is generally rationalized on grounds that users would have the opportunity to learn about the performance characteristics of the system. If there is a unique equilibrium, and if it will always somehow be reached, then solving for this equilibrium need not necessarily concern itself with the processes by which evolution to this equilibrium takes place. However, in a dynamically varying system, where the path towards some eventual steady state is of direct concern, as in the examples given earlier, and if one is interested in altering (improving) this path through control measures, then the assumption of a fully omniscient trip maker must be replaced by a realistic model of how users learn about the system and predict its performance.

In a few instances where this process has been explicitly dealt with, a convenient Markovian assumption has been used, namely that the anticipated travel time on a given day is assumed equal to the actual travel time experienced on the previous day *(12–14)*. Horowitz also has explored simple dynamic travel time adjustment rules in the context of an analysis of the stability of stochastic route choice equilibrium in a two-link network *(15)*. Similar rules were further investigated by Mahmassani and Chang *(6)* in the context of simulation experiments with departure time choice dynamics of urban commuters. However, none of these studies (which were not focussed on the travel time prediction problem anyway) included observations of actual trip maker behavior, obviously a critical ingredient.

Recently, Chang and Mahmassani *(16)* presented a model for this process, with data obtained from an interactive experiment involving real commuters in a simulated, single-route, commuting context. Through the calibration and testing of several alternative specifications, it was found that the latest experienced travel time played a determining role in the formation of the anticipated travel time for the next trip, which in turn is used in adjusting departure time for that trip. In addition, a safety margin, found to depend on the commuter's latest schedule delay and retrievable experience, was used in this adjustment *(16)*. However, in the experiment on which the model was based, commuters were only supplied with information about their own latest experience (i.e., their actual work arrival time, given their departure time for that day) *(7, 8)*. As noted earlier, it is of interest to examine how information availability affects travel time prediction. This question is addressed in this paper by applying the basic modeling framework introduced in the earlier work to the results of a second experiment, in which users were provided not only with their own actual performance on the previous day, but with a complete profile of arrival times corresponding to a spectrum of possible departure times as observed on the preceding day, for each given location within the corridor *(10)*. The second experiment thus corresponds to a complete-information situation (though still for the previous day only, thus still requiring the prediction of a travel time for the next trip), as opposed to the earlier limited-information case.

The experimental details are not of immediate concern in this paper, as they have been reported previously *(8, 10)*. Furthermore, the development of the original model by Chang and Mahmassani *(16)* is not repeated here, though its specification and key implications are reviewed and presented in the context of explaining the new results. A brief review of pertinent experimental details is presented in the next section, followed by the model specification and estimation assumptions and methodology. The estimation results are presented in the fourth section, which is followed by various statistical tests, notably of the hypotheses of parameter stability across user preference groups and geographic sectors. A discussion of the behavioral implications of the model results is then presented, followed by concluding comments in the final section.

THE EXPERIMENT

Following essentially the same experimental procedure developed by Mahmassani et al. *(7)*, the commuting context consists of a four-lane highway used by adjoining residents for their daily home-to-work trip to a single destination such as a CBD or major industrial-office park. This commuting corridor is divided into nine 1-mi sectors, with the common destination located at the end of the last sector. Sectors are numbered from 1 to 9 in order of decreasing distance from the destination, with Sector 1 being the farthest one. Only the first five sectors are designated as residential, with no traffic generation from the remaining areas.

One hundred participants (all commuting staff at the University of Texas at Austin) were assigned equally to the five residential sectors. On the first day, participants were given a description of the commuting context, and asked to supply their departure time as well as their preferred arrival time (in the absence of congestion), with the constraint that arrival after the official (common to all participants) work start time (8:00 a.m.) would not be tolerated. For analysis purposes, participants are categorized into three groups on the basis of their stated preferred arrival time PAT_i (for User i, $i = 1, 2, \ldots, 100$):

Group 1: $7{:}30 \leq PAT_i < 7{:}40$ a.m.
Group 2: $7{:}40 \leq PAT_i < 7{:}50$ a.m.
Group 3: $7{:}50 \leq PAT_i \leq 8{:}00$ a.m.

The departure decisions of all participants form the input to a special-purpose macroparticle traffic simulation model *(17)*, which generates information on the actual (i.e., simulated) arrival time of each participant. On each subsequent day, participants were asked to supply a departure time, given daily information on the system's performance. The information provided to each participant on a given day includes the actual travel time and arrival time experienced by that commuter on the previous day, in addition to the arrival times as experienced on the previous day corresponding to the full array of possible departure times at 3-min intervals from that commuter's origin sector. More detailed description of the experiment can be found in Mahmassani and Tong *(10)*.

MODEL SPECIFICATION AND ESTIMATION METHODOLOGY

The travel time prediction model developed by Chang and Mahmassani *(16)* is part of a modeling framework for dynamic departure time decisions under limited information *(8, 11)*. The same basic specification is adopted here, and modified to incorporate the effect of information availability, by introducing a term for the additional information supplied to system users. The resulting comparability allows insight into the effect of information availability on user judgment and behavior. As discussed by Chang and Mahmassani *(16)*, the specification reflects the dependence of the predicted travel time for the adjustment of the departure time on Day t on (a) the experienced travel time on Day $t - 1$, by far the principal influence on the predicted time, (b) to a much lesser extent, the travel time on Day $t - 2$, with no earlier experience terms coming close to being significant, and (c) a safety margin, intended to minimize the risk of unacceptable arrival in adjusting the departure time, and expressed in terms of the schedule delay on Day $t - 1$ as well as the user's cumulative unsuccessful experience with the facility, as shown hereafter.

When complete information on the previous day's performance is provided to commuters, this additional source can be expected to influence the travel time predicted when adjusting their time of departure. Therefore, an additional term is introduced in order to assess the relative importance of the various information sources and factors influencing travel time prediction.

Travel time prediction and departure time adjustment are intrinsically related in the process under investigation. Regardless of the true nature of the underlying behavioral processes, the empirical analysis must by necessity recognize this interdependence, and accept that a pure predicted travel time simply cannot be observed, at least not in our experiment, nor is it clear how this might be done otherwise. Based on the analysis in Chang and Mahmassani *(16)* of alternative travel time variables and their ability to provide a consistent explanation of the observed departure time behavior, the dependent variable is defined as

$$ETR_{i,t} = PAT_i - DT_{i,t}$$

where

$ETR_{i,t}$ = travel time predicted by User i for the commuting trip on Day t,
PAT_i = stated preferred arrival time for User i, and
$DT_{i,t}$ = selected departure time by User i on Day t.

This definition implicitly assumes that commuters always intend to achieve their initial goal, the preferred arrival time, though difficulties experienced in their search for an acceptable departure time may induce them to increase their respective ranges of tolerable schedule delay *(16)*. The implicit predicted travel time, conditional upon the user's decision to adjust departure time on a particular day, is formulated as follows:

$$ETR_{i,t} = a_1 + a_2 TR_{i,t-1} + a_3 DEL_{i,t} + a_4 TR_{i,t-2} + \delta_{i,t-1} \cdot SFL_{i,t} + (1 - \delta_{i,t-1}) \cdot SFE_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $TR_{i,t}$ is the actual travel time experienced by User i on Day t.

$DEL_{i,t}$ denotes the difference between the experienced travel time on Day $t - 1$ (i.e., $TR_{i,t-1}$), and the specified or supplied travel time information ($ST_{i,t}$), observed on Day $t - 1$, corresponding to User i's departure time on Day t; thus, $DEL_{i,t} = TR_{i,t-1} - ST_{i,t}$.

$\delta_{i,t-1}$ is a binary variable that is equal to 1 if User i is early, relative to the preferred arrival time PAT_i, on Day $t - 1$, and equal to 0 otherwise. This dichotomization is due to earlier results indicating different behavioral responses to early versus late arrivals.

$SFE_{i,t}$ and $SFL_{i,t}$, the safety margins for adjusting to earlier and late departures, respectively, are specified as

$$SFL_{i,t} = (a_5 + a_6 NFL_{i,t-1}) \cdot SDE_{i,t-1}$$
$$SFE_{i,t} = (a_7 + a_8 NFE_{i,t-1}) \cdot SDL_{i,t-1},$$

where

$SDE_{i,t-1}$ = schedule delay for early arrivals relative to PAT_i,
$SDL_{i,t-1}$ = schedule delay for late arrivals relative to PAT_i,
$NFL_{i,t-1}$ = number of unacceptable late arrivals experienced by User i up to Day $t - 1$, and
$NFE_{i,t-1}$ = number of unacceptable early arrivals experienced by User i up to Day $t - 1$.

Note that $NFL_{i,t-1}$ and $NFE_{i,t-1}$ were operationally obtained as the number of departure time changes up to $t - 1$ in response to late and early arrivals, respectively. This procedure assumes that the user will change departure time when the resulting schedule delay exceeds some tolerable level, referred to as the "indifference band" in earlier work *(8)*.

As noted earlier, all of the variables with the exception of $DEL_{i,t}$, which was meaningless in that context, were included in the model specification developed for commuter behavior under the limited-information situation *(16)*. All terms were found to be statistically significant and behaviorally plausible in that experiment. The estimation of a similar specification, modified as described with the additional term, for the complete information situation will therefore allow the assessment of behavioral changes between the two situations.

Estimation of the parameters $a_1, \ldots, a_8$ requires the specification of the structure of the random error terms $\varepsilon_{i,t}$, for all Users $i = 1, 2, \ldots, n$ and Days $t = 1, 2, \ldots, T$. The usual linear model assumptions of identically and independently distributed errors are not appropriate here, because observations of the same individual are likely to be correlated from one day to the next due to unobserved factors that remain constant or change systematically over time. The error structure adopted here follows the same assumption tested in Chang and Mahmassani *(16)* for this problem. In particular, a first-order autoregressive model with contemporaneous correlation across individuals is assumed for the error structure *(18, 19)*, as follows:

$$\varepsilon_{i,t} = \rho_i \cdot \varepsilon_{i,t-1} + \mu_{i,t} \quad \text{(autoregression)}$$
$$E(\varepsilon_{i,t}^2) = \sigma_{i,i} \quad \text{(heteroscedasticity)}$$
$$E(\varepsilon_{i,t}, \varepsilon_{k,t}) = \sigma_{i,k}; \quad i = k; \quad \text{(contemporaneous correlation)}$$
$$E(\varepsilon_{i,t}, \varepsilon_{k,t'}) = 0; \quad i \neq k,\ t \neq t'; \quad i = 1, 2, \ldots, N; \quad t = 1, 2, \ldots, T.$$

Where ρ_i is the correlation coefficient for the ith individual and the $\mu_{i,t}$ values are normally distributed with the following assumptions:

$$E(\mu_{i,t}) = 0;$$
$$E(\mu_{i,t}, \mu_{k,t'}) = \begin{cases} \sigma_{i,k} & \text{for } i, k = 1, 2, \ldots, N \text{ and } t = t' \\ 0 & \text{for } i, k = 1, 2, \ldots, N \text{ and } t \neq t' \end{cases}$$

More detailed discussion of the properties of this model can be found in the literature *(18, 19)*. Under the preceding error structure, parameter estimation was performed using the generalized least squares (GLS) method. The parameters were estimated separately for each residential sector and user group combination defined earlier on the basis of the preferred arrival time. Because in Sectors 4 and 5 the number of departure time changes are too small, only those observations from Sectors 1–3 are used. For the same reason, observations for Preference Group 1 are excluded.

For each estimated equation, overall goodness-of-fit can be assessed by computing Theil's inequality coefficient *(20)* defined as:

$$U = \left\{\sum_{k=1}^{n} [(P_k - A_k)^2/n]/\sum_{k=1}^{n} (A_k^2/n)\right\}^{1/2}$$

where P_k and A_k denote the predicted and actual values, respectively, and n is the total number of observations. The value of this coefficient lies between 0 and ∞, with smaller values indicating better overall model performance.

ESTIMATION RESULTS

The GLS parameter estimates, along with the corresponding t-statistics and Theil's inequality coefficient U, are given in Tables 1 and 2, for each of the six sector-user group combinations considered. The overall goodness-of-fit seems acceptable as indicated by the U value, which is between 0.09 and 0.13, and is smaller than 0.15 in all cases.

Most estimated parameter values have the expected signs; the coefficients of the major components, such as $TR_{i,t-1}$, $DEL_{i,t}$, $SDE_{i,t-1}$, and $SDL_{i,t-1}$, are statistically significant at the 95 percent confidence level. The significance of the coefficient of $DEL_{i,t}$ indicates that users are indeed using the additional information available in this case. However, the coefficient of $TR_{i,t-2}$ is not significantly different from zero for all selected data sets. In addition, its sign is not consistent across data sets. The same is true for $NFL_{i,t-1} \cdot SDE_{i,t-1}$ and $NFE_{i,t-1} \cdot SDL_{i,t-1}$ in this remarkable yet plausible example of the effect of additional information on user behavior. Essentially, the additional supplied information is making it unnecessary to draw on earlier experience, in this case travel time experienced 2 days ago. Similarly, the additional information seems to be reducing the need for the safety margin, which is a device to deal with perceived uncertainty. Clearly, the latter is greater under the limited information situation.

The coefficient of the cumulative experience component of the safety margin for lateness (i.e., $NFL_{i,t-1} \cdot SDE_{i,t-1}$) is significant for Sector 1 only, as indicated by the estimation results for data sets G_2S_1 and G_3S_1. This result appears to suggest that, except for this most distant sector, the need for the commuters to use a safety margin to predict travel time decreases. Further discussion of these questions is presented in conjunction with parameter stability tests and the behavioral implications of the results.

TABLE 1 PARAMETER ESTIMATES FOR USER PREFERENCE GROUP 2

Variable	Parameter (t-value) Data set G_2S_1**	G_2S_2	G_2S_3
CONST	6.624	1.761	8.465
	(6.646)	(3.681)	(5.284)
$TR_{i,t-1}$	0.773	0.903	0.634
	(15.883)	(34.128)	(5.648)
$DEL_{i,t}$	0.360	0.497	0.753
	(17.680)	(41.772)	(19.843)
$TR_{i,t-2}$	-0.053	0.002*	-0.189
	(-2.772)	(0.195)	(-6.394)
$SDE_{i,t-1}$	0.765	0.985	0.865
	(24.155)	(44.635)	(29.166)
$NFL_{i,t-1}$ $SDE_{i,t-1}$	0.022	-0.001*	0.002*
	(3.287)	(-0.200)	(0.322)
$SDL_{i,t-1}$	0.881	0.761	0.641
	(16.530)	(19.335)	(9.259)
$NFE_{i,t-1}$ $SDL_{i,t-1}$	-0.017	0.058	0.015*
	(-2.454)	(3.283)	(1.501)
U	0.10	0.12	0.13
degrees of freedom	208	208	208

*: not significant at 95 % confidence level.
** G_kS_j: User group k in sector j.

TABLE 2 PARAMETER ESTIMATES FOR USER PREFERENCE GROUP 3

Variable	Parameter (t-value) Data set G_3S_1**	G_3S_2	G_3S_3
CONST	4.366	2.268	6.950
	(7.583)	(4.080)	(7.208)
$TR_{i,t-1}$	0.819	0.948	0.765
	(37.238)	(39.801)	(19.388)
$DEL_{i,t}$	0.301	0.377	0.432
	(31.168)	(28.760)	(22.372)
$TR_{i,t-2}$	0.027	-0.044	-0.011*
	(3.022)	(-3.766)	(-0.782)
$SDE_{i,t-1}$	0.750	0.921	0.769
	(34.466)	(40.683)	(21.732)
$NFL_{i,t-1}$ $SDE_{i,t-1}$	0.018	-0.004*	-0.005*
	(6.739)	(-1.021)	(-0.974)
$SDL_{i,t-1}$	0.891	0.921	1.096
	(31.545)	(31.908)	(19.627)
$NFE_{i,t-1} \cdot SDL_{i,t-1}$	-0.010*	-0.017	-0.046
	(-1.127)	(-1.996)	(-3.249)
U	0.12	0.11	0.09
degrees of freedom	262	235	262

*: not significant at 95 % confidence level.
** G_kS_j: User group k in sector j.

Parameter Stability Tests

In order to examine the existence of structural changes in parameter values across user preference groups and geographic sectors, two types of pairwise parameter stability tests are conducted. First, overall tests are performed, in which the hypothesis tested is that all parameters including the constant terms are equal across the two subpopulations under consideration. Next, tests of the equality of selected subsets of parameters are conducted.

The general F-test for linear models is used here to test the hypothesized restrictions on the parameter values under consideration. Details of the test, of which Chow's test *(21)* is a special case, can be found in several standard references *(22, 23)*. Generally, the test procedure involves estimating the model separately with and without the restrictions, and using the estimation results, particularly the sum of squared residuals, to calculate an F-distributed test statistic that can then be compared to the corresponding theoretical value of the F-distribution at the desired significance level.

The results for the pairwise overall parameter stability tests are presented in Table 3. In general, significant differences appear to exist across sectors for the same user preference group, as well as across preference groups within the same sector. However, this conclusion is not uniform, as users in Group 2 appear to exhibit similar parameters across sectors, and group differences appear less clear-cut for users in Sector 3.

The second type of tests addressed the following three subsets of variable coefficients: (a) the travel time variables $TR_{i-1,t}$ and $DEL_{i,t}$, (b) the schedule delay and safety margin terms in response to early arrival, that is, $SDE_{i,t-1}$ and $NFL_{i,t-1} \cdot SDE_{i,t-1}$, and (c) same as the previous item but for the response to late arrival. The results of the pairwise comparisons for each subset of parameters are presented in Tables 4–6. Somewhat unexpectedly, the null hypothesis of parameter equality can be rejected with better than 95 percent confidence for most cases, indicating that different sector and user group conformations appear to place varying degrees of relative importance on the various components that enter into the prediction of travel time and the corresponding adjustment of departure time.

TABLE 3 OVERALL PAIRWISE PARAMETER STABILITY TESTS

Hypothesis *	Computed F-value **	Conclusion ***
$G_3S_1 = G_3S_2$	2.14	Reject
$G_3S_1 = G_3S_3$	3.79	Reject
$G_3S_2 = G_3S_3$	5.68	Reject
$G_2S_1 = G_2S_2$	2.92	Reject
$G_2S_1 = G_2S_3$	1.37	Do not reject
$G_2S_2 = G_2S_3$	0.25	Do not reject
$G_3S_1 = G_2S_1$	1.62	Do not reject
$G_3S_2 = G_2S_2$	2.47	Reject
$G_3S_3 = G_2S_3$	1.67	Do not reject

* Parameters for the two preference group-sector combinations are equal.
** Computed value of the F-test statistic.
*** "Do not reject" : The null hypothesis cannot be rejected at the 95% confidence level.

TABLE 4 PARAMETER EQUALITY TESTS ACROSS PREFERENCE GROUP-SECTOR COMBINATIONS FOR THE COEFFICIENTS OF $TR_{i,t-1}$ AND $DEL_{i,t}$

Hypothesis *	Computed F-value **	Conclusion ***
$G_3S_1 = G_3S_2$	6.14	Reject
$G_3S_1 = G_3S_3$	9.19	Reject
$G_3S_2 = G_3S_3$	21.33	Reject
$G_2S_1 = G_2S_2$	10.54	Reject
$G_2S_1 = G_2S_3$	5.72	Reject
$G_2S_2 = G_2S_3$	0.38	Do not reject
$G_3S_1 = G_2S_1$	8.49	Reject
$G_3S_2 = G_2S_2$	9.15	Reject
$G_3S_3 = G_2S_3$	0.57	Do not reject

* Coefficients of $TR_{i,t-1}$ and $DEL_{i,t}$ for the two preference group-sector combinations are equal.

** Computed value of the F-test statistic.

*** "Do not reject" : The null hypothesis cannot be rejected at the 95% confidence level.

Behavioral Implications

The specification of the travel time prediction model can be decomposed into the following components:

1. Experienced travel time $a_2 TR_{i,t-1} + a_4 TR_{i,t-2}$
2. Supplied travel time information $a_3 \cdot DEL_{i,t}$
3. Response to early arrival $(a_5 + a_6 \cdot NFL_{i,t-1}) \cdot SDE_{i,t-1}$
4. Response to late arrival $(a_7 + a_8 \cdot NFE_{i,t-1}) \cdot SDL_{i,t-1}$

The first two components reflect the influence of experienced travel time and the supplied travel time information on the current prediction of travel time. From the relative magnitudes of the coefficient estimates, the effect of $TR_{i,t-1}$ is much larger than that of $TR_{i,t-2}$ and $DEL_{i,t}$ in all cases. The coefficient a_4 is relatively small compared to a_2 and a_3, and in several cases is

TABLE 5 PARAMETER EQUALITY TESTS ACROSS PREFERENCE GROUP-SECTOR COMBINATIONS FOR THE COEFFICIENTS OF $SDE_{i,t-1}$ AND $(NFL_{i,t-1} \cdot SDE_{i,t-1})$

Hypothesis *	Computed F-value **	Conclusion ***
$G_3S_1 = G_3S_2$	7.83	Reject
$G_3S_1 = G_3S_3$	13.39	Reject
$G_3S_2 = G_3S_3$	15.21	Reject
$G_2S_1 = G_2S_2$	8.73	Reject
$G_2S_1 = G_2S_3$	5.69	Reject
$G_2S_2 = G_2S_3$	3.13	Reject
$G_3S_1 = G_2S_1$	5.13	Reject
$G_3S_2 = G_2S_2$	5.79	Reject
$G_3S_3 = G_2S_3$	5.47	Reject

* Coefficients of $SDE_{i,t-1}$ and $(NFL_{i,t-1} \cdot SDE_{i,t-1})$ for the two preference group-sector combinations are equal.

** Computed value of the F-test statistic.

*** "Do not reject" : The null hypothesis cannot be rejected at the 95% confidence level.

TABLE 6 PARAMETER EQUALITY TESTS ACROSS PREFERENCE GROUP-SECTOR COMBINATIONS FOR THE COEFFICIENTS OF $SDL_{i,t-1}$ AND $(NFE_{i,t-1} \cdot SDL_{i,t-1})$

Hypothesis *	Computed F-value **	Conclusion ***
$G_3S_1 = G_3S_2$	5.01	Reject
$G_3S_1 = G_3S_3$	13.97	Reject
$G_3S_2 = G_3S_3$	7.20	Reject
$G_2S_1 = G_2S_2$	11.13	Reject
$G_2S_1 = G_2S_3$	4.60	Reject
$G_2S_2 = G_2S_3$	2.96	Do not reject
$G_3S_1 = G_2S_1$	4.25	Reject
$G_3S_2 = G_2S_2$	7.64	Reject
$G_3S_3 = G_2S_3$	3.45	Reject

* Coefficients of $SDL_{i,t-1}$ and $(NFE_{i,t-1} \cdot SDL_{i,t-1})$ for the two preference group-sector combinations are equal.

** Computed value of the F-test statistic.

*** "Do not reject" : The null hypothesis cannot be rejected at the 95% confidence level.

not statistically significant, as shown earlier. Essentially, the added supplied information is combined with the most recently experienced travel time to form a predicted value for the travel time that can be anticipated on the next trip, and that provides the basis for the adjustment of departure time. Only in some instances does the earlier experienced travel time exert a significant influence, and one that is an order of magnitude less than that of the most recent experience or supplied information.

Compared to the relative magnitudes of the estimates obtained in the first experiment, under the limited-information situation *(16)*, the coefficient a_2 is smaller here, because it no longer is the only source of information on the previous day's performance. Interestingly, $a_2 + a_3$ is approximately equal to the magnitude of $TR_{i,t-1}$ in the limited-information case. Moreover, the values of a_4 obtained here are smaller than in the first experiment, as expected given that this term is hardly significant when additional information is available.

The third and fourth components reflect the influence of the experienced schedule delay on travel time prediction in the departure time adjustment process. As noted, there is a long-term cumulative experience element and another element for the short-term response to latest experience in forming the safety margin captured by these two components. The coefficients a_5 and a_7 of $SDE_{i,t-1}$ and $SDL_{i,t-1}$, the latest experience terms, are clearly significant. However, the same is not true for the coefficients a_6 and a_8 associated with the cumulative-experience terms $NFL_{i,t-1} \cdot SDE_{i,t-1}$ and $NFE_{i,t-1} \cdot SDL_{i,t-1}$.

The significance and magnitude of a_5 and a_7 indicate that experienced schedule delay plays an important role in travel time prediction and departure time adjustment by commuters. On the other hand, the insignificance of the a_6 and a_8 associated with the cumulative-experience terms (particularly when compared with their significance in the limited-information situation) suggests that the additional supplied information reduces the importance of relying on one's memory or accumulated experience (at least in an active way) in the daily prediction of travel time in the commuting system. Effectively, greater information availability appears to reduce the uncertainty in the travel times perceived by commuters, thereby reducing the need for long-term memory.

In summary, commuters combine their latest experienced travel time with the supplied travel time information in forming a base value for the predicted travel time on the next trip. This base value is adjusted by a safety margin that is primarily governed by the latest experienced schedule delay, in order to protect against unacceptably late or early arrival at the workplace.

CONCLUDING COMMENTS

In this study, an important facet of the complex daily dynamics of commuter behavior in a system evolving towards equilibrium has been examined. This facet is that of user judgment applied to the prediction of travel times in the commuting system, and is one about which little work has been attempted in transportation research. A travel time prediction model developed previously, in conjunction with an experiment in which information availability was limited to users' own experiences, provided the framework for analyzing this phenomenon, using the results of a second experiment in which additional information on the previous day's performance was available. The focus of this study was not so much to develop a definitive operational model of this process as to gain insights into the effect of information availability through the comparative analysis of the model's performance and estimated parameter values. The study was successful in this regard, suggesting that additional information tends to reduce the perceived uncertainty associated with the performance of the system, and is actually used along with the user's latest experience in forming a travel time for the next trip.

Generalizing beyond this specific travel time prediction model, another important direction that is beginning to emerge from this work is that the effect of information availability is not limited to an additive term that would reflect more or less information in a model's specification, but may actually affect the underlying behavioral mechanisms. This result was manifested here, for example, in the virtually insignificant coefficients of the terms reflecting earlier experience. Moreover, other related work by the authors appears to suggest that behavior under greater information availability of the type provided in our experiment is of a more rational (i.e., utility-maximizing) nature than that observed under limited information for which the boundedly rational notion of an indifference band of tolerable schedule delay was found to provide a plausible explanation of the data.

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Nonlinear Utility in Time and Cost of Trips: Disaggregate Results from an Ordinal Methodology

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A new methodology to investigate the linearity of the systematic utility function over time-cost combinations is developed. The approach, based on stated preferences, is unique in that it requires only ordinal preferences from laboratory subjects and assumes only ordinal properties of the utility function. Requiring ordinal rather than intervally scaled preferences provides for more meaningful and cognitively simpler tasks. Assuming only ordinal properties of the utility function defines a best-case scenario for linear performance—if linearity can be rejected under ordinal conditions, it can be rejected under more restrictive conditions. The experimental design leads to geometric, statistical, and predictive tests of ordinal linearity. The methodology is applied to a sample of 12 individuals faced with time-cost combinations of representative morning commute trips, primarily to illustrate the approach. However, even in this preliminary study and using a conservative means of classification, an ordinally linear utility function is rejected in favor of a simple nonlinear specification in half of the subjects. The linear specification cannot be accepted over a nonlinear one for any subject.

The concepts of disaggregate choice and random utility maximization form the basis of many and perhaps the most appealing transportation demand models used today *(1–3)*. These models assume that an individual's preferences can be modeled by a utility function decomposable into a systematic component and a stochastic error term. The systematic utility function V is written as a function of the individual's socioeconomic characteristics and the level of service (LOS) attributes that the transportation alternative offers. For computational convenience, V is written as linear in its parameters:

$$V_j \text{ (alternative } k) = \sum_{i=1}^{N} a_{ji} f_{ji} (Z_{jik}) \qquad (1)$$

where f_{ji} is a component function of the systematic utility function corresponding to the ith of N socioeconomic or LOS variables Z_{jik}, obtained by individual j when choosing alternative k; and a_{ji} is the scaling parameter of this ith function. Two LOS variables used in most analyses of transportation alternatives are the time t and cost c of the alternatives. In practice, the component functions associated with these variables are usually linear and additive, so that Equation 1 becomes

$$V_j \text{ (alternative } k) = \sum_{i=1}^{N-2} a_{ji} f_{ji} (Z_{jik}) + a_{jt}\, t_{jk} + a_{jc}\, c_{jk} \qquad (2)$$

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However, there have been limited propositions to use nonlinear component functions in time and cost. Koppelman *(4)* refers to studies demonstrating that psychological perceptions of time and cost may not be linear in their actual values. Although discrepancies between objective and perceived values can be controlled in a laboratory setting, such studies conducted in the decision sciences have indicated nonlinear utility functions in time and cost *(5–10)*. Limited experiments conducted in the transportation field support the consideration of a nonlinear utility function *(4, 11, 12)*. There are also economically based theoretical arguments *(4, 12)* supporting nonlinear functions. However, the limited empirical results and theoretical arguments are suspect. The studies in the decision sciences deal with larger quantities of time and cost than would be encountered in most applications of transportation demand models. Also, these studies, those performed in the transportation field, and theoretical arguments deal with an intervally scaled utility function. The function used in demand models is claimed to be an ordinal one *(1)*. As argued in the next section, this distinction would invalidate both the theoretical arguments and the empirical methodologies and imply that easier cognitive tasks could be used in the laboratory.

In this paper, ordinally based arguments for considering a systematic utility function whose component functions are nonlinear in time and cost are presented. An empirical study using only ordinally stated preferences for morning commuting options is also described. The results indicate that a linear utility function cannot generally be assumed to describe preferences as functions of time and cost, even when the values of these attributes are small and even when the function is in its least restrictive, ordinal form. The results strengthen the conclusions of previous studies not only by adding more data, but by collecting the data through a more appealing methodology—one that is compatible with the ordinal nature of the utility function and that requires less difficult cognitive tasks of the subjects.

In the next section, current arguments for considering a nonlinear utility function in time and cost are shown to be incompatible with the properties of an ordinal function and ordinally based arguments for considering such a function are presented. The merits of a stated-preference, laboratory-based empirical study are then discussed. Past studies assumed stronger-than-ordinal properties of the utility function and required more difficult cognitive tasks than were necessary. In the following section, the design of the ordinally based empirical study is described. In the last section, the results, based on visual inspection of response surfaces, nonparametric tests of the assumption of a constant marginal rate of substitution, and predictive tests of linear and nonlinear ordinal specifications of the utility function, are presented. Implications and limitations of the results, along with directions for further study, are also discussed.

BACKGROUND FOR AN ORDINAL STUDY

The only LOS variables considered in this paper are time and cost. Therefore, any alternative can be specified by the associated time and cost (t_j, c_j) incurred by individual j when effecting this alternative. Individual j's systematic utility function for an alternative can similarly be specified by $V_j(t_j, c_j)$. From here on, subscript j on time-cost combinations will be dropped, both for simplicity and because the laboratory approach used can control for differences in these combinations among different individuals. With these conventions, Equation 1 becomes

$$V_j(t, c) = a_0 + a_{jt} f_{jt}(t) + a_{jc} f_{jc}(c) \tag{3}$$

where a_0 is a constant encompassing all other fixed terms. The usually encountered Equation 2 can be written

$$V_j(t, c) = a_0 + a_{jt} t + a_{jc} c \tag{4}$$

Theoretical Arguments for a Nonlinear Ordinal Function

Some economists believe that intervally scaled *(13)* utility functions exist and can be measured *(14)*. There have also been several empirical studies investigating intervally scaled utility functions *(6–9)*. But the systematic utility function used in disaggregate choice models is claimed to be an even less restrictive ordinal function *(1)*. There have also been no claims that this function possesses any of the stronger properties, such as intensity or strength of preference, implied by cardinal and intervally scaled functions *(13)*. Although the use of the function is believed to imply stronger properties, it is investigated in its least restrictive ordinal form as a conservative approach to rejecting linearity.

An ordinal function can only indicate a direction of preference. It is a function mapping its arguments into the set of real numbers such that a lower (or higher) real number indicates increased preference *(13)*. Specifically, the ordinal function implies only

$$(t_1, c_1) \,.\, \mathrm{P}_j \,.\, (t_2, c_2) \text{ if and only if } V_j(t_1, c_1) < V_j(t_2, c_2) \tag{5}$$

and

$$(t_1, c_1) \,.\, \mathrm{I}_j \,.\, (t_2, c_2) \text{ if and only if } V_j(t_1, c_1) = V_j(t_2, c_2) \tag{6}$$

where (t_1, c_1) and (t_2, c_2) are two time-cost combinations, $.\,\mathrm{P}_j\,.$ represents "is preferred to, by individual j," and $.\,\mathrm{I}_j\,.$ represents "is indifferent to, for individual j." The symbol $<$ is used instead of $>$ because this convention allows positive coefficients in the utility function when dealing with negatively valued attributes such as time and cost. Therefore, although V really represents a systematic disutility function, the more general term "utility function" is used except when the distinction is needed for clarity.

The implication of the ordinal nature of the utility function is that any monotonic order-preserving transformation of the function yields an equivalent function. That is, if $V_j(t, c)$ represents individual j's utility for time-cost combinations, then $V_j'(t, c)$ also represents individual j's utility for these combinations if $V_j'(t, c)$ is a monotonic transformation of $V_j(t, c)$. For example, if $V_j(t, c)$ could be described by Equation 4, it could also be described by

$$V_j'(t, c) = (a_0 + a_{jt} t + a_{jc} c)^3 \tag{7}$$

However, the linear version is normally used for computational convenience.

The importance of this implication is that it renders inappropriate the current theoretical arguments advanced for a nonlinear utility function in time and cost if the function is to be an ordinal one. These arguments *(4)* are based on the economic concept of nonconstant marginal utilities in time and cost. Because some individuals appear to have marginal utilities for time and cost that depend on the level of these variables already incurred, the marginal utilities of the systematic utility functions $[\partial V(t, c)/\partial t$ and $\partial V(t, c)/\partial c]$ should not be assumed to be constant. Because Equation 4 implies constant marginal utilities, it is not a valid representation of the systematic utility function. But, whether or not the mathematical expression of the marginal utility depends on the level of time or cost incurred depends on which of the equivalent monotonic transformations is used. To see this, the partial derivatives of V' in Equation 7 are taken with respect to time and cost. Although V' is theoretically equivalent to V in Equation 4, analysis of the marginal utilities leads to different conclusions. This difficulty arises from using the derivatives of an ordinal function to indicate something stronger than direction of preference.

However, theoretical arguments for a nonlinear ordinal function can be made by considering the marginal rates of substitution *MRS* instead of marginal utilities. Consider all time-cost combinations of equal ordinal utility. Because the utility is constant, the total derivative of the utility function among these combinations must be zero. After taking the total derivative, setting it equal to zero, and rearranging terms, the *MRS* of cost for time is

$$MRS = dc/dt = \frac{-\partial V(t, c)/\partial t}{\partial V(t, c)/\partial c} \tag{8}$$

Equation 8 implies that if an individual is to be indifferent between one alternative and a second whose time differs from the first by an amount dt, then the necessary change in the second's cost from the first's is given by the ratio of the partial derivatives of the utility function with respect to time and cost. The negative sign indicates that an increase in time requires a decrease in cost and vice versa, because the signs of both derivatives will be identical. To derive this equation, it was only assumed that the appropriate derivatives could be taken. The interpretation is based only on the assumption of the ordinal property of Relation 6.

The importance of using the *MRS* interpretation is that it is unique even for ordinal functions, and the *MRS* of Equation 4 leads to unacceptable conclusions. To see that the *MRS* is unique, let $V'(t, c)$ be related to $V(t, c)$ by a monotonic transformation g—that is, $V'(t, c) = g[V(t, c)]$. Use these definitions and the chain rule to write

$$\frac{\partial V'(t, c)/\partial t}{\partial V'(t, c)/\partial c} = \frac{\partial g[V(t, c)]/\partial t}{\partial g[V(t, c)]/\partial c}$$

$$= \frac{\partial g[V(t, c)]/\partial V(t, c) \times \partial V(t, c)/\partial t}{\partial g[V(t, c)]/\partial V(t, c) \times \partial V(t, c)/\partial c}$$

$$= \frac{\partial V(t, c)/\partial t}{\partial V(t, c)/\partial c} \tag{9}$$

The MRS for V' is the same as that for V, no matter what differentiable transformation is used. Although similar arguments have been made in economics *(15)*, they seem to be overlooked in transportation demand analyses.

The linear utility function used in practice, or any permissible transformation of it, leads to an MRS of cost for time that does not depend on the cost for time already incurred. Specifically,

$$MRS = a_t/a_c \tag{10}$$

But economic intuition and empirical studies indicate that some individuals' strengths of preference for time and cost depend on the levels of these variables already incurred. Although these dependencies cannot be used directly to invalidate a linear ordinal function, they can be used indirectly to reason that the MRS values depend on the levels of these variables. To see this, consider the types of strength of preference that might be exhibited.

Koppelman *(4)* describes an individual who experiences increasingly more discomfort for public transportation as the time of the trip increases. This individual will, therefore, have a stronger preference for a given decrease in travel time dt when this decrease is made from a long trip than when it is made from a short one, because the same decrease relieves more discomfort in the long trip. It follows that the individual should be willing to pay a larger sum dc to reduce the time when the trip is long than when it is short, at least if the original costs of the two trips are the same. Another individual might relax after a while so that an incremental increase will be less onerous; such an individual would pay less to eliminate it as the time incurred increases. A third individual may believe that "a minute is a minute" in the range of times considered and, therefore, would not be willing to change the amount to pay in order to eliminate an increase in time as a function of the amount of time already incurred. The magnitude of the first individual's MRS will be increasing in time, that of the second's decreasing, and that of the third's constant. All of these types of behavior appear plausible, but only the third is permitted by Equation 10 and the linear ordinal utility function from which it was derived.

It is likewise possible that the MRS depends on the level of cost already incurred. One individual may be more sensitive to a given increase in cost when the cost is high than when it is low, while another will be more sensitive when the cost is low. The first individual might be concerned with "spending more than he wants to" for the good, while the second may reason in percentage increases in cost. It follows that the first will pay more to reduce the time when the cost is low than when it is high—that is, have an MRS whose magnitude decreases in cost—and that the second will pay more when the cost is high than when it is low—that is, have an MRS whose magnitude increases in cost. Both behaviors seem plausible, but only that of a third individual, who values increased unit costs equally in the range considered and, therefore, has constant MRS in cost, is permitted by the linear utility function.

There are arguments *(16)* for an individual to possess both increasing and decreasing intervally scaled marginal utilities—and, therefore, both increasing and decreasing MRSs—depending on the amount of attribute incurred. However, these arguments are normally made when large amounts of the attributes are involved. Because this study deals with small quantities, discussion and analysis of plausible descriptions of behavior are limited to those marginal rates of substitution of cost for time that are increasing, decreasing, or constant in time and in cost.

Stated Preference Approach

Most transportation demand studies designed for quantitative, policy assessment contexts use revealed preference data *(1, 17)*. This type of data is usually expensive to obtain, and the analyst has little, if any, control over the LOS attributes acting as independent variables. In general, only one observation can be obtained for a given individual. Also, perceived levels of attributes must be represented by objectively measured levels, leading to the potential difficulties that Koppelman *(4)* discusses.

Laboratory experiments using stated preferences can reduce these difficulties. The analyst poses hypothetical alternatives to a subject, who is asked to state relative preferences among them. Because the alternatives are defined by the analyst, the analyst has complete control over their independent variables. Several observations can be obtained from the same subject. These observations can be responses to the same set of alternatives presented several times or to different sets of alternatives, whose attributes can be varied systematically. Functional forms can, therefore, be determined for each individual. Because the analyst presents the attributes of the alternatives to the subject directly, there is no discrepancy between the analyst's and the subject's perception of the attributes. The general drawback of the stated preference approach is that there is no guarantee that an individual's preferences stated in the laboratory will correspond to the individual's actions implemented in the outside environment. Still, this approach has been used successfully to predict nonlaboratory behavior *(18)*.

Like past theoretical arguments for a nonlinear utility function, however, the transportation studies that have used stated preferences *(11, 16–22)* imply that the systematic utility function has stronger than ordinal properties and, therefore, requires more difficult cognitive tasks than necessary. These studies require individuals to rate the relative value of transportation alternatives by assigning numbers on a scale that is anchored by lower and upper bounds. However, the allowable transformations of the utility functions make assigning such numbers meaningless. Given a number of ratings, many plausible specifications of the utility function could be fit through them by taking some monotonic transformation of the function.

Even if the utility function sought were intervally scaled so that the rating scheme made theoretical sense, it would not be clear that individuals could supply valid estimates of intervally scaled utilities directly. To require only ordinal information of the subjects is cognitively simpler. An analogy in which an individual must decide upon the relative temperatures of two liquids without the aid of a thermometer illustrates this. It would be easier for the individual to determine which of the two liquids is hotter than to assign temperatures to each, even though the individual might be quite familiar with the well-defined concept of temperature. The difference in cognitive difficulty between stating ordinal and intervally scaled preferences for a pair of goods would be even greater, because the individual will have little, if any, operational idea of how to assign a quantitative measure compatible with the interval scale. Researchers in other fields have also expressed concern over the ability to determine valid ratings of preferences directly *(9, 23)*.

The nonlinearity of the systematic utility function in time and cost was investigated empirically using a stated preference approach in a laboratory setting. The approach was chosen because of its appeal for investigating preferences toward systematically varied transportation alternatives. However, unlike previous studies in the transportation field, this study was ordinally based. Such a study required fewer restrictive assumptions of the systematic utility function than one based on intervally scaled data and, therefore, represented a type of best-case test. Moreover, it was compatible with the claim in the literature that the systematic utility function is ordinal. Most important, it required less difficult cognitive tasks of the subjects and, therefore, theoretically led to more valid data. The study was based on the use of preference and indifference statements, which were compatible with an ordinal function through Relations 5 and 6.

DESIGN OF EMPIRICAL STUDY

Protocol

Each subject was asked to consider his daily morning trip to work or school in an abstract mode. The mode was described only generally as not being uncomfortable, and not allowing reading or socializing. The idea was to get the individual to think only about the trade-offs between unproductive travel time and cost. The interviewer then posed the question: "Would you prefer such a trip taking t_k min and costing c_k cents or paying R cents to eliminate the time of this trip?" The values of t_k and c_k were set exogeneously as assessment parameters by the interviewer. The value of the response R was set by the interviewer, but adjusted according to the bracketing method *(9)* until the subject expressed indifference or no preference between $(0, R)$—paying R cents to eliminate the time—and (t_k, c_k). That is, a level of cost R_k was sought with this method such that

$$(0, R_k) \;.\, \mathrm{I}_j \,.\; (t_k, c_k) \tag{11}$$

Using personal interviews and the bracketing method appears to represent deviations from other stated-preference-based transportation studies and should lead to more representative responses. Time was set to zero in the response time-cost pair so that the subject could think of buying out the morning commute time without having to think of an extra time parameter.

Responses to 42 (t, c) combinations were elicited for each individual. The 42 combinations were obtained by taking all combinations of 10, 20, 30, 40, 50, and 60 min with 0, 25, 50, 75, 100, 125, and 150 cents. The upper bounds on these attributes were chosen to coincide with those that the Central Ohio Transit Authority considers for transit trips in the Columbus area. The order of presentation of these 42 combinations was varied among individuals, but the presentation was ordered in such a way that the responses to combinations presented near the end of the session (which lasted about 1 hr on average) were constrained by monotonicity considerations in cost and time by responses presented near the beginning of the session *(24)*. Surprisingly few inconsistencies appeared considering the small differences used in the assessment time-cost combinations. When they did occur, the interviewer would point them out to the subject, who was then allowed to change any responses.

Use of a Response Surface

This type of data leads to an appealing geometric interpretation based on the concept of the response surface *(25)*, which was developed for analysis of choice patterns under uncertainty. The (t, c) pairs can be thought of as points in the time-cost plane. The response R can be thought of as a height above this plane. Because less cost is preferred to more, less R is preferred to more, and the relative heights rank the (t, c) combinations. The three-dimensional response surface above the time-cost plane in time-cost-response space, therefore, represents an ordinal utility function. With the 42 responses, there are 42 points on the surface equally distributed throughout the domain of the time-cost plane considered. The response along the $t = 0$ axis is also known, by construction. The rest of the surface can be estimated by interpolation.

It is convenient to represent the response surface by its isoquants—the projections of constant response in the time-cost plane. If transitivity is assumed, specifically, that $(t_k, c_k) \;.\, \mathrm{I}_j \,.\; (0, R_k)$ and $(t_m, c_m) \;.\, \mathrm{I}_j \,.\; (0, R_k)$ imply $(t_k, c_k) \;.\, \mathrm{I}_j \,.\; (t_m, c_m)$, the isoquants represent indifference curves among (t, c) combinations. Because indifference curves represent loci of equal ordinal utility, the slopes dc/dt of these curves represent the *MRS* developed in Equation 8.

Note that this representation is model free. It assumes no behavioral properties of preferences other than continuity and transitivity, and offers a visual, completely ordinal test of the linearity of the utility function. If the function is linear, the constant *MRS* developed in Equation 10 implies that the isoquants of the response surface should be parallel straight lines. However, given the difficulty associated with the task of psychological introspection necessary for even ordinal statements, perfectly parallel indifference lines are not expected. Rather, large and systematic deviations from linearity as a function of the independent variables time and cost would occur.

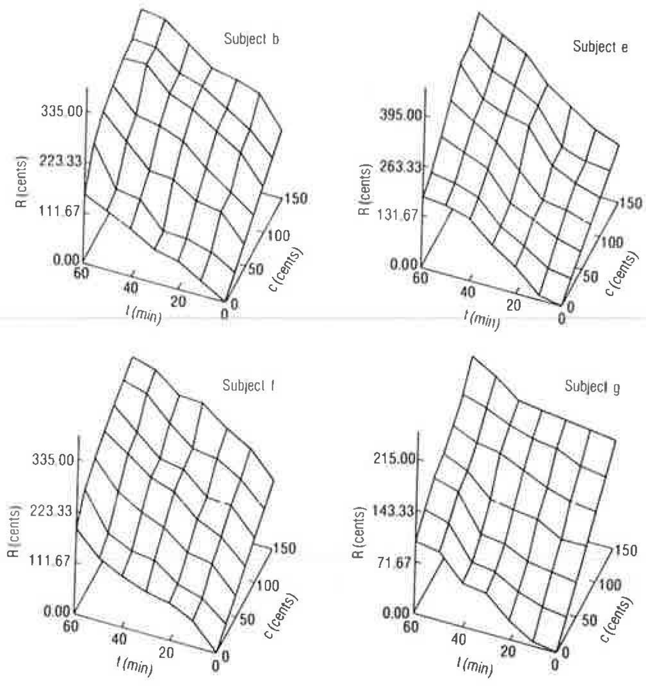

FIGURE 1 Representative response surfaces: (a) Subject b, (b) Subject e, (c) Subject f, and (d) Subject g.

RESULTS

Twelve subjects participated in the empirical study. Nine of these were graduate students in transportation at Ohio State University. The other three were Ohio State graduates with degrees in business administration. Because these 12 participants were chosen on the basis of availability and had a homogeneous educational background, the sample could not be considered representative of the general population. Tests of the general population could be a subject for further study.

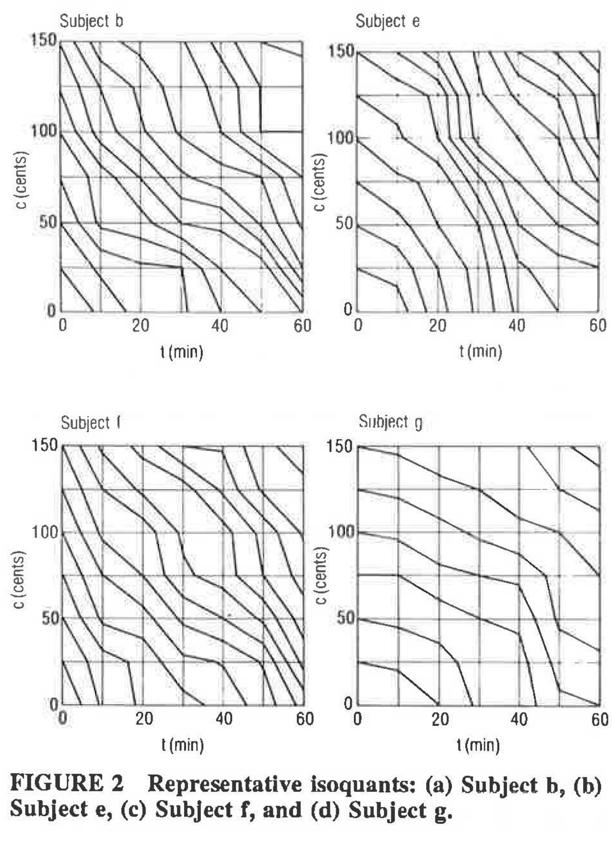

FIGURE 2 Representative isoquants: (a) Subject b, (b) Subject e, (c) Subject f, and (d) Subject g.

Four response surfaces are presented in Figure 1 and their corresponding isoquants in Figure 2. The isoquants of Subjects b and e appear to systematically violate the requirements of linearity; those of Subject f seem to satisfy the requirements; those of Subject g violate the requirements, but not systematically. The isoquants for all 12 subjects can be found elsewhere *(24)*.

Although it is tempting to specify alternative functional forms of the systematic utility function and perform econometric fits of the parameters, it was not known how to do so without requiring stronger than ordinal properties of the utility function. A least squares fit using the 42 indifference statements would require taking the differences between the utility functions, implying that the differences are unique, at least to a positive linear transformation. Using maximum likelihood estimation based upon indifference statements and some specified binary choice model also makes stronger than ordinal assumptions, because these models assign a unique probability to choosing an alternative based upon the difference in the systematic utilities *(1, 2)*. Note that this argument implies that systematic utility functions used in current models based on random utility maximization are not ordinal.

Other quantitative means of investigating the degree to which these stated preferences satisfied the ordinal requirements of a linear utility function needed to be developed through nonparametric tests of calculated marginal rates of substitution and predictive tests of preference using ordinally calibrated parameters.

Nonparametric Test of Constant *MRS*

To estimate the marginal rate of substitution as a function of time and cost, the gridlike structure formed by the sample points in the time-cost plane was exploited. The grid can be seen in Figure 2, where each line represents an axis of either time or cost corresponding to a level that was used as an assessment parameter. The lines form unit boxes, the corner points of which were exogeneously set time-cost combinations for which a response was elicited. The response to a time-cost combination in the interior of one of the unit boxes can be uniquely estimated using linear interpolation among the box's four corner points. Specifically, the response is a function of the responses corresponding to the southwest, southeast, northwest, and northeast corners of the unit box—R_{sw}, R_{se}, R_{nw}, and R_{ne}, respectively; the times corresponding to the west and east edges of the unit box—t_w and t_e, respectively; and the costs corresponding to the south and north corners of the unit box—c_s and c_n, respectively. This interpolation scheme leads to a linearly generated, but perhaps nonplanar, surface above each box (see Figure 1).

Because the response forms an ordinal utility function, Equation 8 can be applied to the response function to determine the *MRS* of any point within the unit box. The *MRS* at the center $[(t_w + t_e)/2, (c_s + c_n)/2]$ of each box was taken, so that the estimate of the magnitude of the *MRS* for a given unit box was

$$MRS = \frac{R_{ne} - R_{nw} + R_{se} - R_{sw}}{R_{ne} - R_{se} + R_{nw} - R_{sw}} \cdot \frac{c_n - c_s}{t_e - t_w} \tag{12}$$

In this way, an estimate was obtained of the *MRS* at all combinations of time levels of 5, 15, 25, 35, 45, and 55 min and cost levels of 12.5, 37.5, 62.5, 87.5, 112.5, and 137.5 cents. These estimates can be found in the literature *(24)*. These estimates would be quite approximate, given the assumption of a linearly generated surface above each box and the arbitrary point within the box at which the estimate was taken. However, these approximations tend to increase the noise level in the estimates. This, coupled with the use of tests on the ranks rather than on the magnitudes of the *MRS* values, leads to a conservative approach in rejecting ordinal linearity of the utility function.

Page's statistic *(26)* on the ranks of the calculated *MRS* values as a function of time at a given level of cost and as a function of cost at a given level of time was used. By calculating the statistic at a fixed level of either cost or time, the influence of these variables on the estimated value of the *MRS* was controlled. The results summarized in Table 1 supported the visual analyses. In Table 1, the null hypotheses are *MRS* values that are constant in time or cost. For those subjects who appeared to have constant *MRS* values in the visual inspection of the indifference curves, midvalue statistics were found. For some subjects (c, d, and g in Table 1) statistics strongly indicating an increasing *MRS* in time were found. For other subjects (a and b) the statistics indicated a decreasing *MRS* in time. Although not as strong, there was some indication of a systematic change of *MRS* as a function of cost—decreasing for Subjects g, j, and k, and increasing for Subject c. Due to the noise involved with generating the *MRS* values, these tendencies were explored further. Predictive tests were developed, consistent with the ordinal nature of the utility function, of the linear and various nonlinear specifications.

Predictive Tests

To describe the predictive test of the linear model, refer again to the unit boxes of the grid formed by the time and cost levels used in assessment. The northeast (ne), northwest (nw), southwest (sw), and southeast (se) corners of a box have coordinates (t_w + 10, c_s + 25), (t_w, c_s + 25), (t_w, c_s), and (t_w + 10, c_s), respectively, where as before, t_w and c_s are the level of time

TABLE 1 PAGE'S STATISTICS ON RANKS OF *MRS* MAGNITUDE

Subject	Alternative Hypothesis on MRS Magnitude			
	(a) Decreasing in Time	(b) Increasing in Time	(c) Decreasing in Cost	(d) Increasing in Cost
a	472.5	409.5	446.0	436.0
b	471.0	411.0	430.0	452.0
c	378.0	504.0	414.5	467.5
d	401.0	481.0	455.5	426.5
e	422.0	460.0	443.0	439.0
f	441.5	440.5	444.5	437.5
g	369.0	513.0	464.0	418.0
h	421.0	461.0	439.5	442.5
i	449.0	433.0	448.9	435.5
j	420.0	462.0	460.0	421.0
k	423.5	458.5	460.0	422.0
l	419.0	463.0	440.0	442.0

forming the west boundary and the level of cost forming the south boundary of the box. Note that by monotonicity the northeast corner of the box must be the least preferred, and the southwest corner the most preferred. For the northwest and southeast corners no preference is normatively apparent. An individual's stated preference between these two corners can be determined through the value of R assigned—the corner with lower R is preferred.

The predictive test revolved about the ability of the utility function to identify correctly the stated preferences between these two corners for each of the 36 unit boxes of the time-cost domain (Figure 2). More comparisons could have been used in the tests (there were 336 nondominated comparisons involving corner points of the unit boxes) but the number of comparisons was limited for simplicity. Comparisons were excluded whose outcomes would be dictated a priori by transitivity and the outcome of a previous comparison. For example, when $(t_k, c_k) \cdot P_j \cdot (t_m, c_m)$ was both stated by the responses and predicted by the utility function, then $(t_k, c_k) \cdot P_j \cdot (t_m + 10, c_m)$ would also be both stated and predicted.

To determine whether the northwest or southeast corner was predicted by a linearly ordinal utility function, Equation 4 and Relation 5 can be used to write that $(t_w, c_s + 25)$ is predicted to be preferred to $(t_w + 10, c_s)$ by Individual j only if

$$g[a_0 + a_{jt}(t_w + 10) + a_{jc}c_s] < g[a_0 + a_{jt}t_w + a_{jc}(c_s + 25)] \quad (13)$$

where g is any monotonic transformation of the linearly specified functions. By taking the inverse of this function, and noting that a_{jt} and a_{jc} must be positive for a disutility function monotonic in time and cost, the predictive conclusion can be written as

$$A < 25/10 \quad (14)$$

where A is a positive parameter equal to the ratio of a_{jt} to a_{jc}. If the value of A is known, whether the northwest or southeast corner of a given box is predicted to be preferred for that value of A, that is, for the calibrated linear model, can be determined.

For each individual, the 42 indifference statements were used to determine 42 values of A. Using the indifference between $(0, R_k)$ and (t_k, c_k) for an individual, Equation 4, Relation 6, and the previous reasoning,

$$A_k = (R_k - c_k)/t_k \quad (15)$$

Note that Equation 15 holds for any monotonic transformation invoked.

Not only how well the linear utility function could predict preferences was of interest, but also whether any poor predictive ability could be associated with behaviorally feasible deviations from the ordinal implications of a constant MRS. As previously stated, only MRS values increasing or decreasing in time or cost were considered as possible alternatives. Although there are many possible functional forms that could lead to these alternatives *(4, 18)*, the predictive ability of power functions of cost and time were used because of their simplicity and use in past studies. Specifically, alternatives were considered to the linear function of the form

$$V_j(t, c) = a_0 + a_{jt}t^{b_{jt}} + a_{jc}c^{b_{jc}} \quad (16)$$

The magnitude of MRS of this form is given by

$$MRS = \left(a_{jt}b_{jt}t^{b_{jt}-1}\right) / \left(a_{jc}b_{jc}c^{b_{jc}-1}\right) \quad (17)$$

Because the a and b parameters are positive for a monotonic disutility function in time and cost, the magnitude of the MRS is increasing, decreasing, or constant in time if b_{jt} is greater than, less than, or equal to 1, respectively, and in cost if b_{jc} is less than, greater than, or equal to 1, respectively.

Values of the exponents b could not be fit because an econometric fitting would imply stronger than ordinal assumptions. A number of indifference statements could theoretically be used to determine values of the independent parameters of Equation 16. Values of b_{jt} and b_{jc} were assigned arbitrarily, however, both for convenience and so that the functions would have the same number of unknown parameters as the linear model, thereby allowing a more direct comparison among the results of the predictive tests. To b_{jt} (b_{jc}) a value of 2 (1/2) was assigned for an MRS whose magnitude was increasing and a value of 1/2 (2) for an MRS whose magnitude was decreasing in time (cost). Along with a value of 1 for constant MRS, this convention led to the nine specifications, one of them being the linear one, summarized in Table 2. Once a specification has

TABLE 2 EXPONENT VALUES b_t, b_c FOR NINE SPECIFICATIONS OF $V(t, c)$

Time Effect on MRS Magnitude	Cost Effect on MRS Magnitude: Decreasing	Constant	Increasing
Decreasing	(1/2, 2)	(1/2, 1)	(1/2, 1/2)
Constant	(1, 2)	(1,1)	(1, 1/2)
Increasing	(2, 2)	(2, 1)	(2, 1/2)

NOTE: $V[t, c; b_t, b_c] = a_0 + a_t t^{b_t} + a_c c^{b_c}$

been chosen, the same arguments can be invoked to show that it is sufficient to know the value of A, the ratio of a_{jt} to a_{jc}, when predicting preference with a utility function given by Equation 16. An individual's stated indifference between $(0, R_k)$ and (t_k, c_k) can again be used to determine for the individual:

$$A_k = \left(R_k^{b_c} - c_k^{b_c}\right)/t^{b_t} \quad (18)$$

A small computer program was written to determine, for each of the 42 values of A, the number of times the specified utility function predicted the same direction of preference as was stated through the responses for each of the 36 northwest-southeast corner pairs. The number of correct predictions was then summed across the 42 A values and divided by the 1,512 (42 × 36) total comparisons to determine an "average percent correct" number of predictions for each of the individual's specified utility functions.

The results presented in Table 3 show that the linear model predicted the direction of preference more than 90 percent of the time for only one individual, between 80 and 90 percent of the time for two other individuals, and less than 70 percent of the time for the remaining nine individuals. For three individuals (a, d, and e) the correct number of predictions was below

TABLE 3 PERCENTAGE CORRECT PREDICTIONS OF NINE SPECIFICATIONS OF $V(t, c)$

	Utility Function Specification, (b_t, b_c)								
Subject	(1,1)	(2,1)	(1/2,1)	(1,2)	(2,2)	(1/2,2)	(1,1/2)	(2,1/2)	(1/2, 1/2)
a	58.3	48.0	61.8	58.6	52.9	60.8	55.9	49.2	65.0
b	61.7	49.8	64.2	59.8	52.4	60.3	59.1	49.5	61.8
c	66.1	80.8	57.1	68.4	75.5	62.3	64.6	78.5	42.9
d	56.0	63.2	50.8	50.7	58.2	48.4	59.7	65.3	52.8
e	55.6	72.0	41.8	56.9	68.2	51.9	50.1	60.6	37.7
f	69.4	59.5	55.4	65.9	62.0	63.0	54.9	54.6	54.1
g	83.3	74.2	78.6	77.5	75.6	74.3	75.7	69.9	77.2
h	86.1	65.8	79.0	64.5	58.5	69.0	80.6	71.8	78.6
i	62.3	61.9	65.6	55.5	57.8	56.9	66.8	67.0	68.1
j	66.9	58.3	67.4	51.4	47.4	57.6	63.3	58.9	67.9
k	60.1	60.5	49.5	60.9	62.3	61.1	57.4	55.5	51.3
l	94.4	73.8	91.3	71.5	61.8	76.7	85.7	72.6	82.2

60 percent, only marginally better than what would be expected by chance. The linear specification was best for only four individuals (f, g, h, and l). No other specification was best for as many individuals, but given that the exponents were arbitrarily chosen and that the arbitrary specification of $b_t = b_c = 1/2$ was best for three individuals (a, i, and j) the indication is that some specification using power functions could have outperformed the linear one. In addition to its generally poor performance in predicting ordinal preferences, compared to its nearest competitor, the linear specification predicted greater than 5 percent more of the preferences correctly only once, for Individual h. Of the eight individuals for whom one of the arbitrary alternative specifications predicted better than the linear one, five (a, c, d, e, and i) exhibited a decrease in the number of correctly predicted preferences of more than 5 percent when the linear specification was used.

Classification of Individuals

Table 3 and visual and statistical analyses can be combined to classify the individuals according to tendency for their *MRS* values to vary systematically with time or cost.

From Table 3 for Individuals a and b, the specifications involving $b_t = 1/2$, that is, those indicating a decreasing magnitude of the *MRS* in time, perform better than the other specifications for any of the three values of b_c. This effect is supported both by the visual inspection of these individuals' isoquants (Figure 2, Subject b) and by the relatively high rank statistic in Column *a* of Table 1. Similarly, the specification using $b_t = 2$ performs better for Individuals c, d, and e than either of the other two alternatives for any value of b_c. The visual analyses (Figure 2, Subject e) and the relatively high statistics in Column *b* of Table 1 support the conclusion that the general trend for these individuals is an *MRS* whose magnitude increases in time. The indication for Individual f is an *MRS* that is constant in time. The specifications with $b_t = 1$ performs best for any value of b_c; the rank statistic is moderate in Columns *a* and *b* of Table 1; and the slopes of the isoquants (Figure 2) show no systematic pattern as a function of time. The rank statistic for Subject g indicates a strong dependence on time. This dependence is supported by the isoquants (Figure 2) except at high values of time, where the pattern of steeper slopes with time changes drastically. Perhaps it is this change in pattern that makes $b_t = 2$ a poor predictor in Table 3. Similar inconclusive results are obtained for Individuals h, i, j, k, and l, which are conservatively classified as having mixed results as a function of time.

Only Individual k exhibits a systematic change in *MRS* as a function of cost. For any of the three possible b_t values, the specification using $b_c = 2$ predicts the greatest number of correct preferences. The corresponding rank statistic in Table 2 (Column *c*) is relatively high. And the isoquants are shallower as the cost is increased. This individual is therefore classified as having an *MRS* whose magnitude decreases in cost. Similarly, only for Individual l is there strong support for a constant *MRS* as a function of the costs considered. The specification with $b_c = 1$ performs best for any value of b_t; the rank statistics are moderate in Columns *c* and *d* of Table 1; visual inspection of the isoquants shows no systematic pattern as a function of cost. For the other 10 individuals, the results from the three analyses are either conflicting or inconclusive. This conflict could result from a preference structure similar to that of Individual g (Figure 2), which is compatible with increasing *MRS* values in some domains and decreasing *MRS* values in others. Because this type of behavior is not investigated here, these individuals can only be classified as having mixed results.

The classification results are summarized in Table 4. Although the procedure for classification was subjective in that the isoquants were visually interpreted and "relatively" high rank statistics were qualitatively determined, those individuals with weak or conflicting results in the mixed results category were classified conservatively. Strong conclusions on the impact of cost on the *MRS* for 10 individuals could not be made. Of the two remaining individuals, one exhibited a constant *MRS*, whereas the other exhibited an *MRS* whose magnitude was decreasing in cost. Strong results were obtained for more individuals when the dependence of the *MRS* on time was examined, and these results tended to discredit the assumption of a linear utility function. Ony one individual strongly showed no dependence in *MRS* on time; two showed *MRS* values whose magnitudes decreased in time; and three showed *MRS* values whose magnitudes increased in time.

TABLE 4 CLASSIFICATION OF SUBJECTS

	Effect on *MRS* of	
Subject	Time	Cost
a	Decreasing	Mixed
b	Decreasing	Mixed
c	Increasing	Mixed
d	Increasing	Mixed
e	Increasing	Mixed
f	Constant	Mixed
g	Mixed	Mixed
h	Mixed	Mixed
i	Mixed	Mixed
j	Mixed	Mixed
k	Mixed	Decreasing
l	Mixed	Constant

None of the 12 individuals could be classified as exhibiting an ordinally linear utility function, whereas 6 could be classified as not having such a function due to a dependence on time or cost. Even if the two individuals showing no dependency on one of the variables and mixed results on the other, and the four individuals showing mixed results on both variables were classified as linear, the evidence is that other than linear specifications can be expected even at relatively low levels of time and cost.

DISCUSSION

The discussion of this study can be divided between its methodological and empirical components.

At the methodological level, a new approach has been developed and demonstrated for investigating the linearity of the systematic utility function for the time and cost of trips. The methodology would be easy to generalize to any two continuous LOS variables. It uses a laboratory, stated-preference-based approach and, therefore, allows economical collection of data that lead to systematic investigations of individuals' utility functions. Unlike approaches based on revealed preferences, an investigation of the utility function over ranges of the independent variables is easily obtained.

However, the methodology is different from others using stated preferences for transportation demand analyses in that it is ordinally based. It assumes only ordinal properties of the utility function and requires only ordinal preferences from the laboratory subjects. Only ordinal properties of the utility function are assumed because the function is claimed to be ordinal in the literature. Although current discrete choice models imply stronger than ordinal properties, a methodology that would be applicable if the function could eventually be used in an ordinal manner was desired. Also, because the methodology was used to investigate the rejection of properties, the less restrictive ordinal properties represent a conservative, best-case benchmark. Data that cannot support ordinal properties cannot support stronger ones. Finally, by requiring ordinal rather than intervally scaled preferences from the subjects, the cognitive difficulty of their tasks is reduced and the tasks are made more meaningful. These procedures should produce more valid data.

Past studies have used goodness-of-fit measures and tests of statistical significance when analyzing results. Because these types of analyses imply stronger than ordinal properties of the utility function, they were not used. Even so, three different tests of linearity could be developed at the ordinal level. Supporting results with different tests increases the confidence placed in conclusions drawn from them. One potential area of research could be devoted to understanding the situations in which the tests can give conflicting results and refining the tests so as to reduce the possibility of such situations.

At the empirical level, the pool of scarce but significant data indicating that utility functions are generally not linear in time and cost, even for the small levels encountered in urban travel, has been increased. None of the subjects could be confidently classified as exhibiting a linear function, whereas six could be confidently classified as exhibiting systematic deviations from linearity. Although the sample was not chosen to represent any general population, the absence of an across-subject consistency is somewhat disturbing. The practical implication is that even though nonlinear utility functions should be considered, a general specification does not appear possible.

Even if the results were representative of the general population, the deviations from linearity in opposite directions for different individuals and the better predictive ability of the linear utility function in the aggregate would not justify use of a linear function. The motivation for disaggregate choice theory is a behavioral one, and the utility function must be capable of describing preferences at the individual level if the models are to be marketed as being behaviorally based. Disaggregate choice theory acknowledges the possibility of different parameter values of the utility function for different segments of the population. It would be reasonable to allow different specifications, as well. Further research would be necessary to determine the distribution of functional specifications across the population and of those parameters that can be used to stratify the specifications. The methodology used in this study could prove useful in this task.

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A Method for Estimating Long-Term Changes in Time-of-Day Travel Demand

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One of the desired features of a travel demand model is an ability to estimate not only 24-hr traffic volumes but also their distributions during the day. In this paper, usefulness of the recently proposed person-category trip generation model to address this issue is examined. A method to estimate time-of-day productions and attractions is proposed. The time-of-day travel profiles of homogeneous groups of persons from Lodz, Poland, and Baltimore, Maryland, are examined. Category-specific, time-of-day travel patterns appear consistent for different subareas within a given metropolitan area, whereas the differences in travel profiles among person-categories are high. This modeling approach provides insight into long-term changes in time-of-day travel distribution as a result of such trends as increase in female employment, increase in average age of the population, increase in automobile availability level, and so on. Forecast and policy implications are also discussed.

Time-of-day variations in daily traffic are of particular interest to transportation planners and engineers. Most of the transportation problems in urban areas are strongly correlated with the magnitude of the peak traffic and could be significantly alleviated if there were a way to distribute traffic more evenly during the day. For obvious reasons, peaking in travel demand is unavoidable, and traffic volumes during the morning and afternoon peak constitute criteria for the geometric design of the transportation network.

Several studies have been performed in different metropolitan areas around the world to examine and better understand peaking phenomenon in daily traffic. A typical result of such studies could be an hourly histogram of daily traffic similar to Figure 1, which presents time-of-day traffic variations in Melbourne, Australia *(1, 2)*. The traffic profiles in other cities show regularities similar to that from Melbourne, although the shapes of actual distributions vary from city to city. For example in Lodz, Poland, the morning peak hour between 7:00 and 8:00 a.m. accounted for 10.3 percent of daily traffic and the afternoon peak hour between 4:00 and 5:00 p.m. accounted for 10.8 percent of daily traffic *(3)*. Because the morning traffic revealed less directional variability, the morning rather than the afternoon peak volumes were used to determine road geometry in Polish cities *(3)*.

In earlier studies, time-of-day travel profiles were often complemented by additional profiles for different trip purposes or profiles differentiated by the transportation mode used for a given trip. In recent approaches using disaggregate choice modeling methodology, time of day may be included as an additional element of a choice facing Individual *i*. For example, probability of Individual *i*'s choosing to travel to Activity (trip purpose) *p* by Mode *m* and during Time Period *t* can be described as a product of respective conditional probabilities.

$$P_i(p, m, t) = P_i(p)P_i(m/p)P_i(t/m, p) \tag{1}$$

where

$P_i(p)$ = probability that Individual *i* travels during the day to Purpose *p*,
$P_i(m/p)$ = probability that Individual *i* chooses Mode *m* for Purpose *p*, and
$P_i(t/m, p)$ = probability that Individual *i* travels during the specified Time Period *t* for Purpose *p* on Mode *m*.

High heterogeneity of the urban population is the reason why the probabilities vary from person to person, thus making practical applications difficult, particularly in a context of forecasting the peak-period and off-peak traffic volumes. Therefore, it seems reasonable to link time-of-day travel modeling with modeling of trip generation. An extended trip generation model able to estimate travel demand not only for a 24-hr period, but for any peak or off-peak period as well, could be sought. One such model could be a zonal regression model with the coefficients recalibrated for time of day instead of the 24-hr period. However, well-known criticism directed toward this class of models (estimating generations, not attractions) would apply as well.

Another candidate technique could be category analysis. A representative example in this class of models is the 108-household-category model developed by Wooton and Pick in 1967 *(4)*. However, any household-based model will face an unavoidable basic problem of a high heterogeneity of the household. Detecting regularities among categories of households treated as a whole in their trip-making behavior with respect to trip purpose, mode, or time of day is difficult if not practically unfeasible. The large variety of households types, sizes, and structures will always primarily influence all these joint characteristics.

A person-based category model appears a logical candidate for this analysis of the time-of-day travel because of a clear link between individuals' outside-home activities and resulting travel. Kutter's idea of constructing hourly histograms of travel *(5)* is a successful attempt to prove that different segments of the population have distinctly different patterns of their activities and travel.

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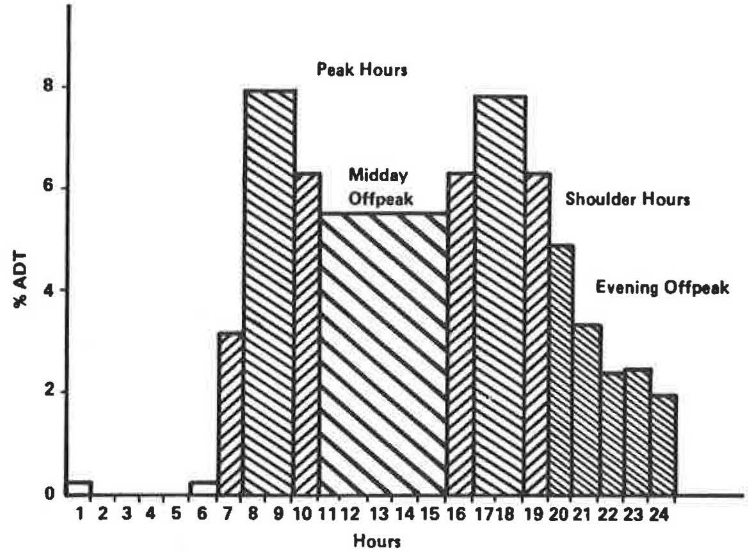

FIGURE 1 Typical hourly traffic pattern—weekday *(1, 2)*.

In this paper the suitability of the person-category modeling approach to analyze time-of-day regularities in travel behavior of homogeneous groups of individuals is examined. The model is an extension of the 15-category trip generation model developed by Supernak for Polish cities in 1979 *(6)* as well as the 8-category trip generation model developed by Supernak et al. for American cities in 1983 *(7)*. The main objectives of this paper are

1. To investigate consistency of time-of-day travel patterns related to homogeneous categories of individuals,
2. To analyze the potential for using these patterns to estimate peak-period and off-peak trip generation and distribution, and
3. To discuss regularities in time-of-day travel patterns in the context of the utility maximization principle.

APPROACH AND DATA

The major difference between the person-based modeling approach and other approaches is the fact that grouping of the individuals (potential or real travelers) into groups of similar behavior is based on revealed differences in trip-making behavior (in terms of mobility, mode choice, time-of-day preferences, etc.) rather than on those individuals' automatic affiliation to the same geographic area (zonal level) or the same family (household level). Generalization of the observed behavior of any disaggregate analysis unit (household or person) is unavoidable in any application context, and can be accomplished much more easily and more adequately if (a) a proper market segmentation takes place, and (b) market segments are identifiable and predictable *(8)*.

The advantages of the person-based travel demand approach over the household approach were discussed elsewhere *(7, 9)*. They include better behavioral background (same analysis unit over all modeling stages), easier forecasts (prediction of population segments is independent of the changes in family formations), and significant reduction of data needed (and consequently lower cost of travel surveys). In the specific context of this paper, the major advantage of the person-based approach is its fundamental ability to analyze and interpret time-of-day travel patterns at all. Similar patterns applied to such heterogeneous clusters as household would not have much merit or use.

Two data sets were used for the analysis reported in this paper. The first set was gathered in 1973 in Lodz, the second largest agglomeration in Poland (about 1 million inhabitants), and the second one in 1977 in the Baltimore, Maryland, metropolitan area (with population also about 1 million). The sizes of the data sets were different—about 40,000 persons in Lodz versus about 1,800 persons in Baltimore. The relatively small size of the Baltimore data set was the reason why some aspects of the analysis reported in this paper could be performed only on Lodz data. Both surveys used home interviews as a data-gathering technique.

The methodology of creating homogeneous person-categories was also similar in both studies. Both models were developed in stages (two in the Lodz case, three in the Baltimore case) in order to gradually reduce the number of person-categories by eliminating variables that revealed least explanatory power at each stage. Cluster analysis and analysis of variance were used as statistical techniques to accomplish this goal. The analysis resulted in relatively small numbers of person-categories—15 in the case of Lodz and 8 in the case of Baltimore. The procedure of developing person-categories is described in more detail in Supernak et al. *(7)*.

The final categories in the Lodz study were defined as follows:

Category	*Description*
1	Primary school children
2	High school students
3	College students
4	Youth, nonstudents, and nonemployed
5	Housewives
6	Retired and pensioners
7	Male employees, family with a car
8	Male white collar workers, no car
9	Male blue collar workers, no car

Category	Description
10	Male service workers, no car
11	Female employees, family with a car
12	Female white collar workers, no car
13	Female blue collar workers, no car
14	Female service workers, no car
15	Preschool children

For Baltimore the categories were defined as follows:

Category	Description
1	Persons <18 years of age
2	Employed, age 18 to 65, car never available
3	Employed, age 18 to 65, car sometimes available
4	Employed, age 18 to 65, car always available
5	Nonemployed, age 18 to 65, car never available
6	Nonemployed, age 18 to 65, car sometimes available
7	Nonemployed, age 18 to 65, car always available
8	Persons >65 years of age

The most significant variables explaining differences in travel behavior were

Lodz (Poland)	Baltimore, Maryland
Age	Age
Employment status	Employment status
Automobile ownership	Automobile availability
Sex	
Type of employment	

The criteria for homogeneity of old categories to be combined into a new category were different in both studies. For the Lodz study, two Categories i and j were considered similar only if their 35-element vectors of partial trip rates differentiated by (a) base (home-based origin, home-based destination, non-home-based); (b) trip purpose (work, education, other purposes); and (c) time of day (midnight to 5:30 a.m.; 5:30 a.m. to 8:30 a.m.; 8:30 a.m. to 2:00 p.m.; 2:00 p.m. to 5:00 p.m.; 5:00 p.m. to midnight) satisfied the following criteria of similarity:

1. Correlation coefficient $r_{ij} \geq 0.900$,
2. Slope $0.75 \leq b_{ij} \leq 1.25$, and
3. Intercept $|a_{ij}| \leq 0.10$.

In the Baltimore study, each category was represented by a 15-element vector of partial trip rates differentiated by (a) base (home-based origin, home-based destination, non-home-based), and (b) trip purpose (work, education, shopping, personal business, social, recreation). Thus, the time-of-day criterion was not introduced as a criterion of similarity of travel patterns in Baltimore. This lack was mainly due to scarcity of the Baltimore data. Introducing this criterion in the Lodz study was probably responsible for the significance of the variable employment type (white collar workers, blue collar workers, service employees) because of differences in working hours between white and blue collar workers (mostly 8:00 a.m. to 4:00 p.m. for office employees versus 6:00 a.m. to 2:00 p.m. for factory workers in Poland).

For this paper, the Lodz study was more meaningful than the Baltimore one because (a) time of day was a primary criterion of category definition, and (b) the data set was much larger.

RESULTS OF THE STUDY

The results of both studies are presented in Figures 2–4. Figure 2 shows hourly trip histograms for a sample of 9 out of 15 person-categories in Lodz. There are separate profiles for (a) trips originated at home (HO), (b) ended at home (HD), and non-home-based (NHB). If the data set is large enough, this separation may help with directional analysis of traffic volumes generated by each category, for example, toward the central business district (CBD), away from CBD, and non-CBD-oriented. Figure 3 shows a sample of joint hourly trip histograms for just three categories in Lodz representing three fundamentally different activity and trip patterns for (a) preemployment, (b) employment, and (c) postemployment segments of the urban population. Figure 3 shows joint hourly trip histograms during the 24-hr period between 4:00 a.m. and 4:00 a.m. the next day. (This presentation should probably be recommended instead of the period between midnight and next midnight because of late returns home from such activities as entertainment or personal visits.) The four geographic areas within Lodz are rings differentiated by the transit travel time to the CBD: Zone 1, <15 min; Zone 2, 15 to 30 min; Zone 3, 30 to 45 min; and Zone 4, >45 min. Figure 4 shows a joint trip histogram of Categories 1–8 in Baltimore.

The basic objective of this analysis is to answer two questions: (a) are there significant differences among person-categories in terms of their time-of-day travel patterns? and (b) are the category-based time-of-day trip characteristics consistent geographically? Visual inspection of Figures 2–4 suggests positive answers to both questions. Hourly trip histograms are indeed category-specific in both geographic contexts (in Lodz, Poland, and Baltimore, Maryland). Note that person-categories with no obligatory activities (e.g., work, education) try to plan their discretionary activities (shopping, personal business, recreation, etc.) during off-peak periods, more convenient for travel. This applies to Category 6 in Lodz (Figures 2 and 3) and to Categories 5–8 in Baltimore (Figure 4). Hourly trip histograms from both cities could be approximated by smooth, continuous functions.

A brief comment on the findings presented in Figures 2–4 can be made in terms of the utility maximization principle, commonly applied in disaggregate travel demand methodology. Persons participating in discretionary activities try to minimize disutility associated with travel (time expenditure, discomfort, etc.) by traveling during the off-peak periods. Moreover, several discretionary activities (shopping, park recreation, etc.) have their highest utility also during the off-peak period (e.g., quicker service at stores, more sunshine during the middle of the day). Thus, persons who select the off-peak period for their activity and associated travel are acting rationally because they are trying to maximize their overall utility of the activities while at the same time minimizing their disutility of travel.

For employed persons and students, the choice scenarios are greatly limited. The utility of being at work (or, to a lesser degree, at school) is commonly perceived as high but is normally restricted to a specific period during the day. The high utility of the activity is commonly able to offset even the highest disutility of travel during peak periods. (Changing the job or relocating will not be seen as the person's immediate reaction to the congestion problems experienced during travel to work.)

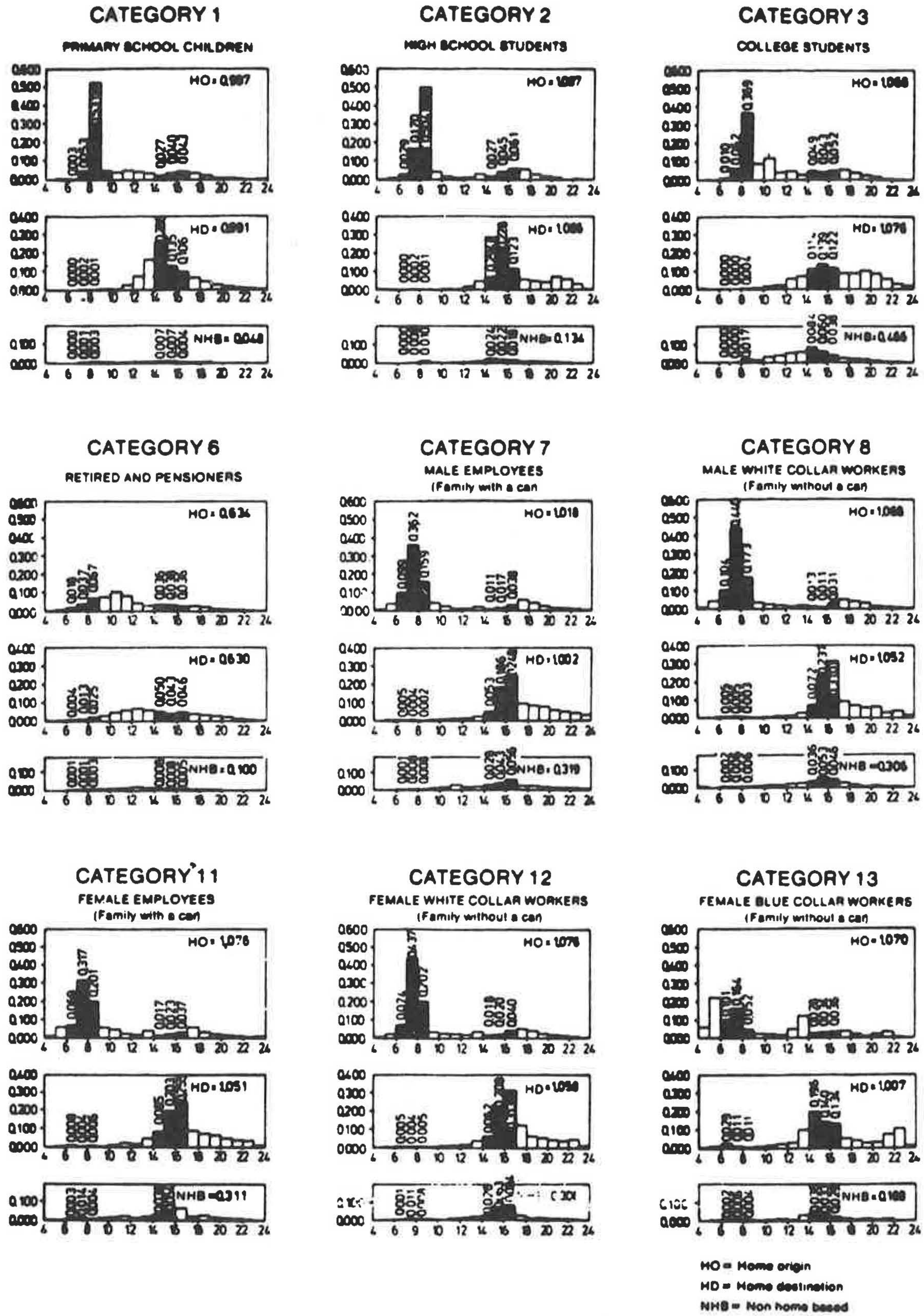

FIGURE 2 Hourly trip histograms of 9 out of 15 person-categories in Lodz, Poland. Total of *HO* + *HD* + *NHB* constitutes the daily trip rate for Category *i*.

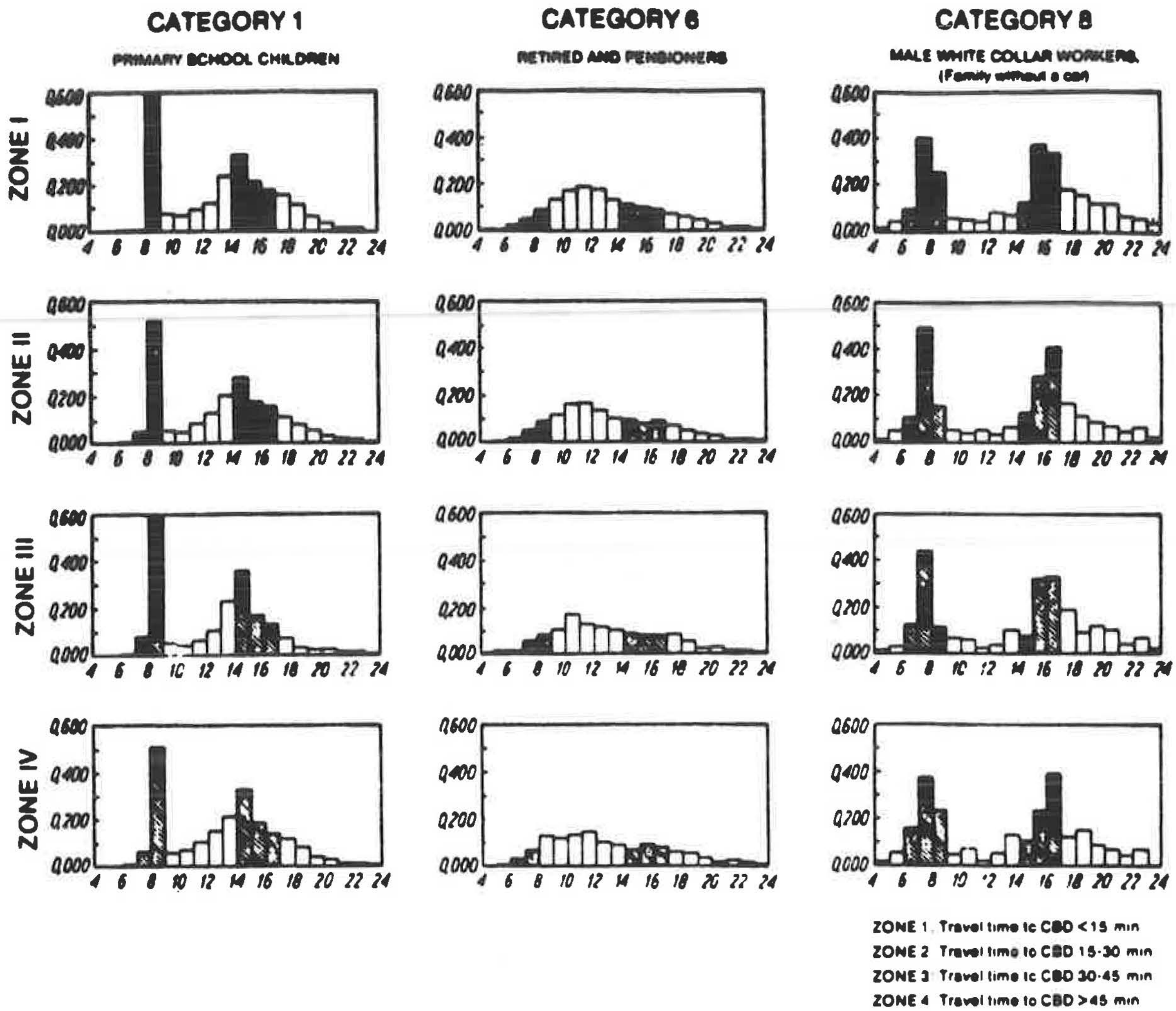

FIGURE 3 Hourly trip histograms of three representative person-categories from four zones of Lodz, Poland. Total of hourly rates amounts to daily trip rate N_i.

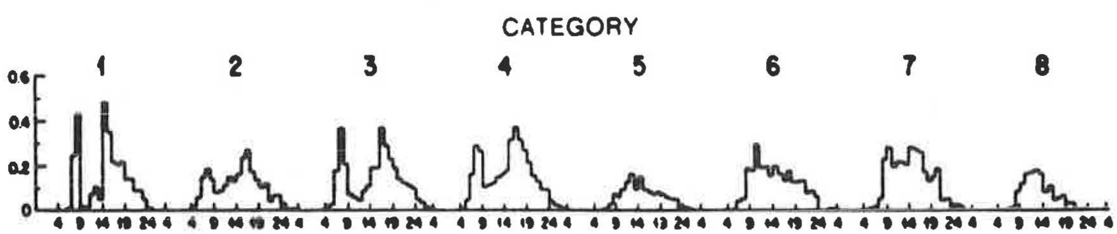

FIGURE 4 Hourly trip histograms of eight person-categories from Baltimore, Maryland. Total of hourly rates amounts to daily trip rate N_i.

Results of the statistical analyses presented in Tables 1 and 2 are in agreement with the previous impression about the observed regularities in category-based time-of-day travel patterns (Figures 2–4). For the purpose of this analysis, all hourly histograms from Figure 3 had to be standardized, that is, each hourly value represented the revealed probability of travel during a given period similar to Figure 1 (with a total of 1 for the 24-hr period).

Table 1 confirms the hypothesis that there are significant differences in hourly trip histograms among person-categories. Time-of-day trip distributions of Category 1 (primary school children), Category 6 (retired persons), and Category 8 (male white collar workers) are significantly different from the expected population distribution in all cases analyzed ($\alpha = 0.01$).

Table 2 shows that area differences in category-specific time-of-day trip profiles are significant only in 2 out of 12 cases analyzed ($\alpha = 0.01$). The geographic stability of travel profiles within homogeneous categories is an interesting finding considering the dramatically different geographic contexts analyzed (central city versus suburbs in Lodz). Similar analysis for

TABLE 1 RESULTS OF THE KOLMOGOROV-SMIRNOV TEST FOR GOODNESS OF FIT OF TIME-OF-DAY DISTRIBUTION FOR CATEGORIES 1, 6, AND 8 TO EXPECTED CATEGORY TIME-OF-DAY TRIP DISTRIBUTION (DATA FROM LODZ, POLAND)

Zone	Characteristic	Category 1	Category 6	Category 8
	n	1422	1913	878
1	D_{max}	0.114	0.136	0.179
	D_{crit}	0.042	0.037	0.055
	n	4357	4108	2024
2	D_{max}	0.115	0.155	0.194
	D_{crit}	0.025	0.024	0.036
	n	618	646	187
3	D_{max}	0.127	0.134	0.257
	D_{crit}	0.066	0.066	0.119
	n	1747	979	370
4	D_{max}	0.068	0.127	0.210
	D_{crit}	0.039	0.052	0.085

n = sample size (number of trips); $D_{max} = \underset{i=1}{\overset{24}{\mathrm{Max}}} |F_i - S_i|$; $\alpha = 0.01$

Baltimore could not be performed because of the limitations of the size of the data set. It is not clear, therefore, to what extent the travel pattern regularities from Lodz could be generalized for West European or American cities.

APPLICATION OF THE TIME-OF-DAY TRAVEL PROFILES TO TRIP GENERATION AND DISTRIBUTION

The trip interchange $T_{ij}(t_1, t_2)$ between Zones i and j during a specified Time Period $t_2 - t_1$ can be described as follows:

$$T_{ij}(t_1, t_2) = f_1[P_i(t_1, t_2), A_j(t_1, t_2), C_{ij}(t_1, t_2)] \quad (2)$$

where

$P_i(t_1, t_2)$ = production of Zone i during Period $(t_2 - t_1)$,
$A_j(t_1, t_2)$ = attraction of Zone j during Period $(t_2 - t_1)$, and
$C_{ij}(t_1, t_2)$ = generalized cost of travel between Zones i and j during Period $(t_2 - t_1)$.

The attractions $A_j(t_1, t_2)$ can be known from empirical studies of the time profiles of arrivals at major employment places and schools, and to a lesser degree at other potential attraction points (parks, banks, etc.). If it is assumed that for each trip purpose p the corresponding shares $S_p(t_1, t_2)$ or arrival probability functions $g_p(t_1, t_2)$ are known, then

$$A_j(t_1, t_2) = \sum_p A_{jp}(t_1, t_2) \quad (3)$$

$$A_{jp}(t_1, t_2) = A_{jp}S_p(t_1, t_2) \quad (4)$$

or

$$A_{jp}(t_1, t_2) = A_{jp} \int_{t_1}^{t_2} g_p(t)\,dt \quad (5)$$

where A_{jp} is the total daily attraction of Zone j for Purpose p.

Productions $P_i^{HB}(t_1, t_2)$, on the other hand, do not depend on area characteristics but rather on characteristics of trip makers who try to satisfy their outside-home activities at some time during the day. The category-specific hourly trip histograms can now be useful for estimations of $P_i^{HB}(t)$, which otherwise could be rather difficult to estimate.

$$P_i(t_1, t_2) = P_i^{HB}(t_1, t_2) + P_i^{NHB}(t_1, t_2) \quad (6)$$

The home-based production of Zone i, $P_i^{HB}(t_1, t_2)$, can be estimated as

$$P_i^{HB}(t_1, t_2) = L_i \sum_{k=1}^{n} \left[\alpha_k \left(\sum_{t=t_1}^{t_2} H_{kt}^{HB}\right)\right] \quad (7)$$

summed over the hourly histogram, or, if normalized travel profiles are used,

$$P_i^{HB}(t_1, t_2) = L_i \sum_{k=1}^{n} \left[\alpha_{ik} N_k^{HB} \left(\sum_{t=t_1}^{t_2} h_{kt}^{HB}\right)\right] \quad (8)$$

where

L_i = population of Zone i,
α_{ik} = share of Category k in Zone i,
N_k^{HB} = home-based daily trip rate of Category k,
H_{kt}^{HB} = hourly histogram of daily trip rate of Category k, and
h_{kt}^{HB} = normalized histogram of daily trip rate of Category k.

The h_{kt} satisfy the normalization condition

$$\sum_{t=0}^{24} h_{kt} = 1$$

If histograms h_{kt} could be substituted by a probability function $h_k(t)$ such that

$$\int_0^{24} h_k^{HB}(t)dt = 1,$$

then Equation 8 becomes

$$P_i^{HB}(t_1, t_2) = L_i \sum_{k=1}^{n} \left[\alpha_{ik} N_k^{HB} \int_{t_1}^{t_2} h_k^{HB}(t)dt\right] \quad (9)$$

$$P_i^{NHB}(t_1, t_2) = f_2[A_i(t_1, t_2)] \quad (10)$$

During the 24-hr period, the following balancing condition has to hold (if trips crossing the cordon of the study area are ignored):

$$P = A = Y \quad (11)$$

where

P = total daily trip production (generation) in the city (sum of all zonal productions, both HB and NHB);
A = total daily trip attraction in the city; and
Y = total daily number of trips made (anywhere) by inhabitants of all zones.

Thus non-home-based production will be

$$P^{NHB} = A - P^{HB} \quad (12)$$

Trip total Y will amount to

$$Y = L \sum_{k=1}^{n} (\alpha_k N_k) \quad (13)$$

where L, α_k, N_k are as before but for the entire city. It could be reasonable to assume that

$$P\Big|_{t_1}^{t_2} = A\Big|_{t_1+\Delta t}^{t_2+\Delta t} = Y\Big|_{t_1}^{t_2} \quad (14)$$

where $\Delta t = \bar{t}_{ij}(t_1, t_2)$ = the average travel time between a pair of zones during the analyzed period $t_2 - t_1$ for the entire city.

Thus, balancing conditions for period $t_2 - t_1$ for the entire city are

$$L \sum_{k=1}^{n} \left[\alpha_k N_k^{HB} \int_{t_1}^{t_2} h_k^{HB}(t)dt\right] + f_2[A(t_1, t_2)] = \sum_{p=1}^{m} A_p \int_{t_1+\Delta t}^{t_2+\Delta t} g_p(t)dt \quad (15)$$

or

$$L \sum_{k=1}^{n} \left[\alpha_k N_k \int_{t_1}^{t_2} h_k(t)dt\right] = \sum_{p=1}^{m} A_p \int_{t_1+\Delta t}^{t_2+\Delta t} g_p(t)dt \quad (16)$$

This equation can be used to adjust f_2 and $g_p(t)$.

TABLE 2 RESULTS OF THE KOLMOGOROV-SMIRNOV TEST FOR GOODNESS OF FIT OF TIME-OF-DAY DISTRIBUTION FOR ZONES 1–4 TO EXPECTED ZONE TIME-OF-DAY TRIP DISTRIBUTION (DATA FROM LODZ, POLAND)

Category	Characteristic	Zone 1	Zone 2	Zone 3	Zone 4
1	n	1422	4357	618	1747
	D_{max}	0.024	0.013	0.063	0.024
	D_{crit}	0.043	0.025	0.066	0.039
6	n	1913	4108	646	979
	D_{max}	0.051*	0.018	0.059	0.106*
	D_{crit}	0.037	0.024	0.066	0.052
8	n	878	2024	187	370
	D_{max}	0.043	0.019	0.018	0.071
	D_{crit}	0.055	0.036	0.119	0.085

*)Difference significant at α = 1% level

The time-of-day travel forecasts can be made by introducing corresponding forecast variables L', α'_k and adjusting functions f'_2 and $g'_p(t)$. This procedure should give a modeler an approximate idea about the expected changes in traffic volumes not only during the 24-hr period but during any peak or off-peak period as well.

It is clear that such changes as increasing female employment, increasing automobile availability, and gradual aging of the society and changes in family structures have had a profound effect on changes in both overall daily volumes and time-of-day distribution of the daily traffic during the recent decade or two. This process continues, and will influence, among other traffic characteristics, time-of-day travel profiles. The person-category method is able to account for these long-range changes, and thus provide useful information about the scale of the desired changes in time-of-day traffic distribution in the future. It will be up to the transportation policy makers to decide to what extent the expected demand should be satisfied, or the anticipated peak-hour behavior modified [by, for example, some specific transportation systems management (TSM) actions].

The complete equilibration process is, of course, much more complicated than the theoretical considerations from this paper (e.g., than Equations 15 and 16) would suggest. The basic category analysis assumption is that travel characteristics of homogeneous categories of individuals will remain unchanged over time. This assumption seems reasonable for the off-peak traffic when the system functions below its capacity. In the case of peak-period traffic, the situation may often be quite complex. First, the model coefficients calibrated for existing conditions may already reflect some modifications in travel patterns resulting from some degree of the oversaturation of the transportation network in some places. Second, even if it is not the case (which would not be a realistic assumption for most North American and European cities), the forecast year may indicate deterioration of the currently satisfactory travel conditions in several areas. In that case, the forecast made by using person-category travel profiles would represent desired volumes rather than real ones. Traffic assignment forecast would have to reduce these volumes to the level determined by the equilibrium conditions on the specific elements of the network. For the travelers it will mean either (a) necessarily eliminating some noncompulsory travel during peak period; (b) searching for a more convenient route or mode of traveling (e.g., abandoning a car in favor of transit if it enjoys preferential treatment), or (c) accepting increased delays and consequently also increasing length of peak periods.

It is felt that, in spite of its simplification, the person-category time-of-day volume estimation would be useful not only for an assessment of likely changes of traffic volumes in the future but also for policy analyses of possible countermeasures (such as different TSM strategies, among them flexible work hours) to be applied in situations where the traffic situation is expected to deteriorate. Today, in most western cities and probably in several cities elsewhere a significant part of the vital elements of transportation systems operates under saturated or oversaturated conditions during peak periods. Therefore, peak-period travel profiles for specific person-categories may represent an unnegotiable need for travel, independent of its inconvenience. It will be unrealistic to assume that many of these trips would disappear if the travel conditions deteriorate even more. Rather, a mode switch consideration or acceptance of longer delays and longer peak periods would be more likely options. Therefore, category-specific time-of-day profiles may appear more stable over time than the complexity of the phenomenon [influence from (a) traveler, (b) network, and (c) traffic] would indicate. Previous studies about actual responses in time-of-day travel to specific policies *(11, 12)* will be helpful for any extended application of the approach proposed in this paper.

CONCLUSIONS

1. Extension of the person-category trip generation model by using category-specific time-of-day travel patterns appears a useful approach to estimate peak and off-peak traffic volumes in metropolitan areas. Time-of-day travel patterns are found to be significantly differentiated among person-categories and relatively stable for representatives of the same person-category residing in different subareas of the metropolitan area studied.
2. Time-of-day regularities in travel represent a rational behavior of groups of persons who try to maximize their utility of outside-home activities and minimize the disutility of associated travel. The resulting time-of-day travel patterns are strongly related to the time-of-day changes in both utilities of activities and disutilities of travel. These patterns illustrate a fundamental difference between highly constrained behavior of employed persons and students, and a relatively unconstrained behavior of persons involved in discretionary outside-home activities only.
3. Person-category time-of-day travel analysis can provide a better insight into the peaking phenomenon, useful in travel studies and forecasts. Category-specific travel patterns can provide a base for estimation of the scale of the potential long-range changes in traffic volumes for any time-of-day period. By estimating potential demand for additional traffic volumes during peak periods, this approach can help develop appropriate solutions to best handle the network oversaturation problems by adequate TSM strategies or protransit policies.

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Discrete/Continuous Analysis of Commuters' Route and Departure Time Choices

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An analysis of commuters' choices of routes and departure times is undertaken using a discrete/continuous econometric modeling structure. The modeling system is estimated with morning work trip data collected in State College, Pennsylvania. The estimation results provide interesting insights into the behavioral aspects motivating route and departure time choices and underscore the need for proper econometric specification in discrete/continuous model structures. Overall, the model estimations provide surprisingly good fits and show promise for applications in a traditional user equilibrium framework.

The problem of peak-period traffic congestion has served as the primary motivation for countless research studies. Such efforts have ranged in focus from highway capacity analyses, including intersection studies and coordinated traffic signal strategies, to studies of trip-making behavior. The congestion remedies suggested by these studies have given rise to new highway construction, various traffic capacity improvements (e.g., highway widening and improvement and automation of signal timings), high-occupancy-vehicle lanes, car- and vanpooling, and marketing efforts supporting public transportation. Although such remedies have met with varying degrees of success, peak-period traffic congestion continues to be one of the most persistent problems facing the transportation profession.

In this paper, an important behavioral aspect of the peak-period congestion problem, travelers' choices of route and departure time, is considered. In the past few years, there has been a healthy level of research devoted to the general area of departure time and route choice. For example, an econometric modeling approach was adopted by Cosslett *(1)* and Abkowitz *(2)* for departure time choice, and by Hendrickson and Plank *(3)* for the choice of departure time and mode. Hendrickson and Kocur *(4)*, Hendrickson et al. *(5)*, De Palma et al. *(6)*, and Mahmassani and Herman *(7)* studied departure time in the context of user equilibrium for a single route. Extensions of some of these modeling efforts resulted in the inclusion of a route choice component, but on a limited scale as expressed by the equilibrium approaches of De Palma et al. *(6)*, Mahmassani and Herman *(7)*, and by the econometric simulation approach of Ben-Akiva et al. *(8)*. Although a number of past studies have provided valuable insight into the route and departure time choice decision-making process, they have all developed methodologies that treat departure time as a discrete variable as opposed to a continuous one. The argument in support of the discrete treatment of this variable is that travelers can only distinguish among a few prevailing traffic conditions over a specified departure period. However, by discretizing departure time an arbitrary structure of time intervals is being imposed on the decision model. In this paper, a model that treats departure time as a continuous variable and thereby avoids any a priori restrictions on the modeling approach is developed.

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ECONOMETRIC FRAMEWORK

In developing an appropriate econometric structure, first a probabilistic route choice model for travelers' automobile commutes to work is specified. Let the utility provided by each route be a linear function for each traveler,

$$U_i = \beta(ETT_i) + \sigma(RC_i) \tag{1}$$

where

U_i = utility provided by Route i to the traveler;
ETT_i = expected travel time on Route i;
RC_i = vector of route specific characteristics such as number of traffic signals, queue lengths, and so on, for Route i; and
β, σ = estimable parameters.

If a disturbance term is added to Equation 1 such that $V_i = U_i + \varepsilon_i$ is assumed to be distributed with a generalized extreme value (GEV) distribution, it can be shown *(9)* that the route choice probabilities are given by the standard multinomial logit model,

$$P(i|R) = \frac{\exp U_i}{\sum_j \exp U_j} \tag{2}$$

where $P(i|R)$ is the probability of selecting Route i from the set of available Routes R, and other terms are as previously defined.

With the route choice model specified, the specification of a continuous departure time model can be considered. The departure time, for each commuter, is defined from the following identity:

$$DT = WST - TT - WAT - DC \tag{3}$$

where

DT = departure time;
WST = work start time;
TT = travel time;
WAT = work access time (i.e., walking time from parking location to work location); and
DC = delay cushion defined as the time difference between WST and arrival time (i.e., $DC = DT + TT + WAT$).

For the purposes of this analysis, it is assumed that WST and WAT are exogenous to the route and departure time choice process. Therefore, the aspects of departure time determination that are controllable by commuters include travel time and the delay cushion. In similar work, Mahmassani and Chang *(10)* analyzed the individual's departure time through a dynamic boundedly rational framework, but one that was based only on a schedule-delay acceptability mechanism.

Most previous work has viewed route travel time as a factor beyond a commuter's control. In other words, under specified flow conditions, all commuters face the same route travel times. However, in reality, this assertion is valid only under extremely congested conditions. Under most flow conditions, individual commuters have considerable control over their travel times by their abilities to alter driving speeds, risk-taking behavior, and reaction times in the traffic stream and at intersections. Given this condition, a linear model of individual commuters' choice of travel time is defined by

$$TT_i = \tau + \alpha(RC_i) + \theta(SE) + \eta(VC) + \upsilon_i \tag{4}$$

where

TT_i = work trip in-vehicle travel time (min) on Route i;
RC_i = vector of route specific characteristics for Route i (e.g., flow rate);
SE = vector of socioeconomic characteristics of the commuter;
VC = vector of vehicle characteristics used to commute;
υ_i = disturbance term; and
$\tau, \alpha, \theta, \eta$ = estimable parameters.

From an econometric perspective, the estimation of Equation 4 gives rise to a classic problem of selectivity bias because route and travel time choices are interrelated decisions. To illustrate this problem, consider an origin-destination pair connected by two routes, one a freeway and the other an arterial. It is unrealistic to assume that the travel time behavior of people observed to be using the freeway will be identical to that of people using the arterial. Observed freeway users may tend to be faster drivers, in general, because the freeway route offers them the potential to drive at much higher travel speeds. Hence, on the basis of observed route users, a censored sample exists because there is no way to know how fast a freeway user would have driven had he or she selected the arterial or how fast an arterial user would have driven had he or she selected the freeway. Estimation results are biased because users observed on any specific route represent a nonrandom sample formed from a systematic route selection process.

Numerous econometric methods have been developed in recent years to correct such a selectivity bias problem. A comprehensive review of such methods as they apply to transportation is presented by Mannering and Hensher *(11)*. The method selected for use in this study is the expected value method, which has been successfully applied by Dubin and McFadden *(12)* and by Mannering and Winston *(13)*. To apply this method, Equation 4 is rewritten, conditioning on the choice of Route i,

$$TT = \tau + \alpha \sum_{k=1}^{n} (RC_k)\phi_{ki} + \theta(SE) + \eta(VC) + \upsilon \tag{5}$$

where TT is the travel time conditional on choice Route i, n is the total number of route alternatives, and ϕ_{ki} is an indicator variable that equals 1 when $k = i$ and 0 otherwise.

To arrive at consistent estimates of Equation 5, the choice indicators (ϕ_{ki}) are replaced by the estimated probabilities from the route choice model (Equation 2). Thus, every route-specific variable included in the travel time equation is replaced by its expected value, which is the summation over all route alternatives of the route's selection probability multiplied by its corresponding route-specific attribute.

The remaining component of Equation 2 necessary for departure time prediction is the delay cushion, which is defined as the difference between the work start time and the actual commuter arrival time. A linear model is defined,

$$DC_i = \eta + \psi(RC_i) + \lambda(SE) + \delta(PREF) + \omega_i \tag{6}$$

where

DC_i = delay cushion (min) on Route i,
RC_i = vector of route specific characteristics,
SE = vector of commuters' socioeconomic characteristics,
$PREF$ = commuters' preferences for early or late arrivals,
ω_i = a disturbance, and
$\eta, \psi, \lambda, \delta$ = estimable parameters.

As was the case with the travel time model, the delay cushion model must also be corrected for possible selectivity bias, because it is unreasonable to assume that the selection of route and delay cushion are independent decisions. Consistent estimates of Equation 6 are obtained as discussed for the travel time model by replacing all route-specific independent variables by their expected values (see Equation 5).

EMPIRICAL SETTING AND SAMPLE DESCRIPTION

To estimate the specified route, travel time, and delay cushion models, a survey of morning commuters in the State College, Pennsylvania, metropolitan area was undertaken. To simplify data collection and subsequent empirical analysis, one origin-destination pair was evaluated. The origin was a large residential development in suburban State College and the destination was the Pennsylvania State University and surrounding downtown State College. The residential area comprises mostly multiple-story apartment complexes and the destination is a highly concentrated area of educational and business activity comprising less than 1 mi^2.

Three distinct and diverse routes connect the selected origin-destination pair. One is a four-lane major arterial with center turning lane and a 35-mph posted speed limit. Another is a two-lane rural highway with 12-ft lanes, 4-ft paved shoulders, and a design speed of 45 mph. The third is a four-lane expressway designed to Interstate standards. This diversity of routes makes the selected origin-destination pair particularly well suited to route and departure time choice modeling.

The morning commute survey was designed as a trip log in which respondents provided a variety of information on their most recent work trip, including route choice; make, year, and model of car used; maximum driving speed; departure time; work arrival time; scheduled work starting time (if any); preferred arrival time at work; safety belt use; automobile occupancy; and walking time from parking lot to work location. In addition, general socioeconomic information was collected, including income, age, occupation, marital status, and number of children. In the last week of April 1986, the survey was administered as a postage-free mailback questionnaire to 505 randomly selected origin residents. Although there was nearly a 40 percent response rate, improperly completed forms and respondents with work start times outside of the studied morning peak period produced 151 usable observations. The summary statistics for the usable sample are presented in Table 1.

Table 1 reflects the relatively short commute times that are typical for such a small metropolitan area. The socioeconomic characteristics are also typical for the graduate students and young professionals that dominate the survey sample.

In addition to the commuter survey, extensive traffic-related data were collected for each of the three routes connecting the origin and destination. This information included flow rates, intersection queue lengths, peak-hour volumes, route lengths, and traffic signal characteristics (phasing, cycle times, etc.). All of this information is potentially useful for the route characteristic variables specified in Equations 1, 4, and 6.

ESTIMATION RESULTS

The route choice model as specified in Equations 1 and 2 was estimated first. The estimation results of this model are presented in Table 2. As mentioned earlier, this model specifies the probability of a commuter's selecting one of the three alternate routes (i.e., arterial, rural route, or expressway) described in the previous section.

The first variable included is the route's expected travel time. Expected travel time is defined to be the travel time predicted by the Bureau of Public Roads' (BPR) equation

$$ETT = T_0\left[1 + \alpha\left(\frac{V}{C}\right)^{\beta}\right]d \tag{7}$$

TABLE 1 SAMPLE SUMMARY STATISTICS (Means or Percentages)

Home to work in-vehicle travel time (minutes)	11.68
Home to work distance (miles)	4.81
Age (years)	32.95
Household income (dollars)	25,860
Percent male/female	63/37
Percent married/single	42/58
Percent using safety belts	71
Vehicle occupancy	1.2
Percent automobiles less than 5 years old	66
Percent with fixed work start times preferring early arrival (positive delay cushions)	60
Percent with fixed work start times preferring on-time arrivals (zero delay cushions)	37
Percent with fixed work start times preferring late arrival (negative delay cushions)	3

where

ETT = expected travel time (min);
T_0 = travel time (min/mi) at zero flow (i.e., at speed limit);
V = peak-hour volume (veh/hr) measured from field surveys;
C = capacity of the route;
d = distance from origin to destination; and
α, β = route specific parameters that are functions of speed limit and capacity.

The values of α and β used in estimation are obtained from the Branston study *(14)* in which transferable values are presented for different highway types.

The expected travel times calculated by Equation 7 may vary from commuter to commuter because their precise destinations within the general Pennsylvania State University and downtown State College destination area are considered. In other words, travel on local access streets is considered in addition to the three line-haul routes discussed earlier. Expected travel times are therefore distance weighted to account for travel on highway segments of varying capacity and speed limit. All variables in the estimated models take into account this precise destination consideration.

As a final point, it is important to note that the use of expected travel times as defined in Equation 7 avoids endogenicity problems that would be encountered if actual travel times were used. This problem arises because travel time and route choice decisions are interrelated and a correlation between an explanatory variable (travel time) and the disturbance term would exist. [See Mannering and Hensher *(11)* for a discussion of this problem in a discrete/continuous modeling framework.]

Returning to the coefficient estimates presented in Table 2, *ETT* has the anticipated negative effect on route selection probabilities. Moreover, estimation results indicate that higher-income commuters (those earning $30,000 or more) find travel time to be more onerous than their lower income counterparts. This presumably reflects the higher value of time of high-income commuters.

The percentage of coordinated traffic signals has a positive influence on the probability of route selection, indicating that commuters value the reduction in the variance of travel time resulting from signal coordination. Finally, the number of traffic signals increases the probability of route selection for individuals with flexible work start time. This suggests a willingness among flexible-time commuters to accept a higher travel time variance and to gamble for the lowest travel time route. (Recall that expected travel times are explicitly considered in the model.) Statistically, the route choice model performs well with relatively low standard errors and a high degree of log-likelihood convergence.

The travel time model is estimated by ordinary least squares and the dependent variable is the in-vehicle work trip travel time in minutes. The estimation results for uncorrected models and models corrected for selectivity bias (i.e., Equations 4 and 5, respectively) are presented in Table 3. The difference between corrected and uncorrected coefficient estimates underscores the importance of correcting for possible selectivity bias.

For specific coefficient estimates, the expected travel time as defined for the route choice model is a strong predictor of actual travel time. This variable is actually capturing a number

TABLE 2 ROUTE CHOICE COEFFICIENT ESTIMATES (Standard Errors in Parentheses)

Variable		Coefficient
Expected travel time if income less than $30,000 (in minutes)*		-0.585 (0.091)
Expected travel time if income $30,000 or more (in minutes)*		-0.753 (0.155)
Percent of traffic signals coordinated		0.043 (0.021)
Number of traffic signals if flexible work start time		0.126 (0.053)
Number of observations		151
Log likelihood	at zero	-241.15
	at convergence	-106.45

*See text for precise definition.

TABLE 3 TRAVEL TIME MODEL ESTIMATES, UNCORRECTED AND CORRECTED FOR SELECTIVITY BIAS (Standard Errors in Parentheses)

Variable	Coefficient Estimate Uncorrected	Coefficient Estimate Corrected
Constant	8.407 (1.562)	5.079 (1.79)
Expected travel time (in minutes)*	0.189 (0.074)	0.247 (0.079)
Flow rate (in vehicles per hour, per lane)*	0.00463 (0.00159)	0.00977 (0.00213)
Sex (1 if male, 0 if female)	-0.414 (0.341)	-0.470 (0.328)
Safety belts (1 if used, 0 if not used)	-1.416 (0.649)	-0.873 (0.636)
Age (1 if 30 years old or less, 0 otherwise)	-0.677 (0.588)	-0.851 (0.566)
Vehicle vintage (1 if 5 years old or less, 0 otherwise)	-0.738 (0.624)	-0.555 (0.593)
Number of observations	151	151
R-squared	0.150	0.216

*See text for precise definition.

of physical characteristics of the route, including speed limit, capacity, and distance (see Equation 7). The other route-specific variable in the model is the instantaneous flow rate defined as the observed flow rate over the 5-min interval that occurs 5 min after the commuter's reported departure time, transformed into equivalent vehicles per hour per lane. Understandably, this variable is strongly positive, indicating that increasing instantaneous flow rate increases commuters' travel times.

Three socioeconomic variables were included in the model. The sex indicator variable confirmed a priori expectations that males tended to drive faster than females. The safety belt indicator variable produced a negative coefficient, suggesting that safety belt users tended to drive faster. This result lends some support to Sam Peltzman's famous hypothesis concerning the tendency of safety belt users to drive more recklessly, thereby mitigating the potential benefits of safety belt usage *(15)*. Finally, the age indicator coefficient indicated that younger commuters tend to drive faster than older ones.

The only vehicle characteristic included in the model was the vintage. This variable indicates that newer vehicles, with more sound bodies and steering, are driven faster than older vehicles. Unfortunately, the sample was not large enough to explore the differences among high-performance, compact, intermediate, and large cars.

The delay cushion model was defined only for those respondents that actually had fixed work start times. Because the sample included many researchers and self-employed professionals, only 90 of the 151 respondents had fixed work start times. Because the route choice behavior of these respondents may differ somewhat from the full sample estimates presented in Table 2, the route choice model was reestimated using only the 90 commuters with fixed work start times. The specification is identical to the earlier route choice model, of course excluding the flexible work start time traffic signal variable, and the estimation results are presented in Table 4. The route choice probabilities estimated from this model will be used to produce the expected values needed to correct for selectivity bias in the delay cushion model. For the 61 respondents with no fixed work start times, Equation 3 does not apply. For these commuters, departure times are simply their stated preferred arrival times minus their travel and work access times. The stated preferred arrival time is exogenous to the route and departure

TABLE 4 ROUTE CHOICE COEFFICIENT ESTIMATES FOR PARTICIPANTS WITH FIXED WORK START TIMES (Standard Errors in Parentheses)

Variable		Coefficient
Expected travel time if income less than $30,000 (In minutes)*		-0.368 (0.073)
Expected travel time if income $30,000 or more (In minutes)*		-0.340 (0.157)
Percent of traffic signals coordinated		.0073 (0.011)
Number of observations		90
Log likelihood	at zero	-98.88
	at convergence	-72.88

*See text for precise definition.

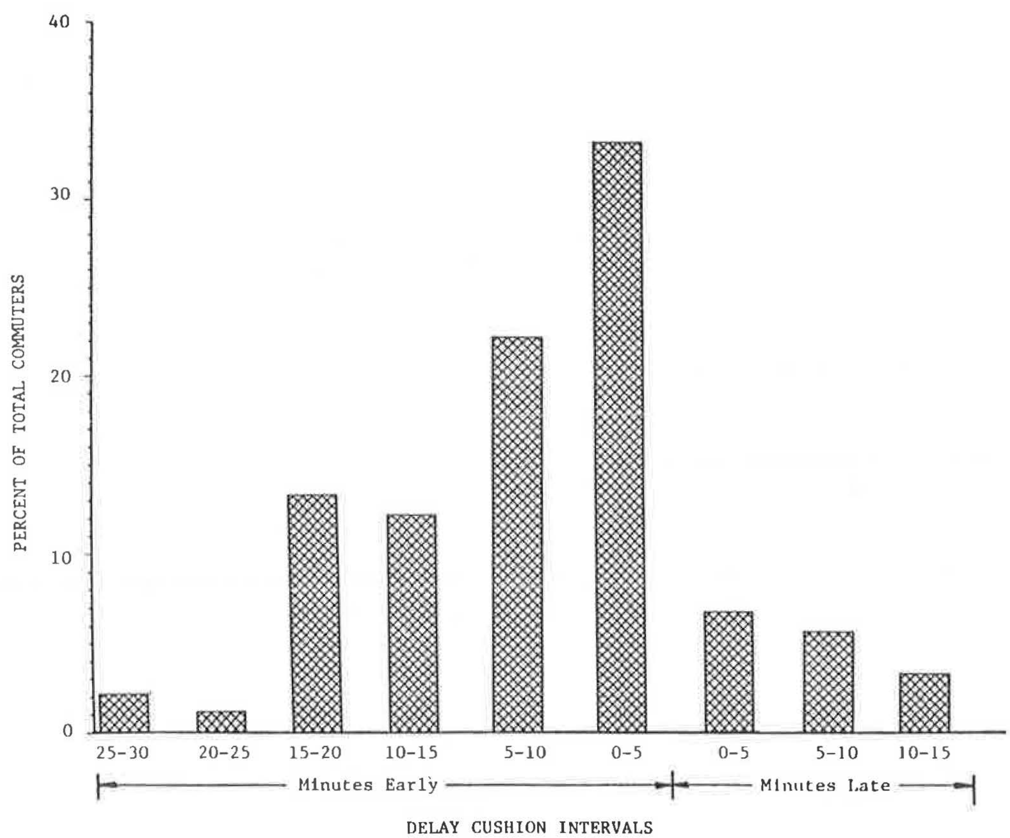

FIGURE 1 The distribution of actual delay cushions.

time choice decision-making process. A similar treatment was used by Mahmassani and Chang *(16)*, for whom preferred arrival times were supplied by commuters.

The dependent variable in the delay cushion model is the difference between the work start time and actual arrival time in minutes and will be positive if the commuter arrives early and negative if the commuter arrives late. The actual observed distribution of these delay cushions is shown in Figure 1. The coefficient estimates for the regression model, both corrected and uncorrected for selectivity bias, are presented in Table 5.

The only route specific variable included in the model is the expected travel time, defined as before. The coefficient is negative, indicating that the longer the commute the less the delay cushion. This negative sign may be an outgrowth of the rather short commuting distances that the sample of travelers experienced. That is, because absolute variance in travel time is fairly small due to the short travel distances, commuters tend to decrease their delay cushions to compensate for longer in-vehicle travel times, knowing that the likelihood of a late arrival is rather small. It would be interesting to reestimate this model with a longer, higher-variance commute and to reassess the delay cushion and expected travel time relationships.

The socioeconomic variables include income and age. The income coefficient is negative, indicating that higher-income people prefer shorter delay cushions (i.e., have a higher value of time). The age coefficient is positive, suggesting that older workers tend to be more risk-adverse by choosing longer delay cushions.

The final variables are commuters' preferences for early, on-time, or late arrivals. These preferences are accounted for by indicator variables with on-time implicity set to zero. The coefficients of the preferred-early and preferred-late arrival indicator variables are of plausible sign and are highly significant statistically. Overall, the R^2 value of this model is surprisingly high considering the high variance likely to be present in all delay cushion data.

ESTIMATION NOTES

The inclusion of flow-dependent variables in all models gives rise to two important estimation concerns. The first is one of selectivity in that traveler behavior in response to prevailing flows is observed only for the departure time actually chosen. However, unlike the route choice selectivity bias problem discussed earlier, there is no theoretical basis for assuming that the behavioral characteristics of individuals departing at different times will systematically differ. Thus, although the sample is censored in that individuals are not observed departing at all

TABLE 5 DELAY CUSHION MODEL ESTIMATES, UNCORRECTED AND CORRECTED FOR SELECTIVITY BIAS (Standard Errors in Parentheses)

Variable	Coefficient Estimate: Uncorrected	Coefficient Estimate: Corrected
Constant	-1.288 (3.979)	0.497 (4.108)
Expected travel time (in minutes)*	-0.137 (0.161)	-0.268 (0.187)
Income (in thousands of dollars)	-0.091 (0.082)	-0.091 (0.081)
Age (in years)	0.174 (0.093)	0.172 (0.093)
Preferred early cushion (1 if prefer to arrive before work start time, 0 otherwise)	9.078 (1.424)	9.119 (1.417)
Preferred late cushion (1 if prefer to arrive after work start time, 0 otherwise	-7.047 (3.95)	-7.248 (3.919)
Number of observations	90	90
R-squared	0.406	0.415

*See text for precise definition.

available times, there is no reason to believe that it is censored nonrandomly, and as a result selectivity bias and the associated endogenicity of flows are not an issue with respect to departure times.

The second point is one of endogenicity in the more traditional sense. As specified by the equilibrium condition in Equation 1, flow determines demand but is itself an outcome of demand. This relationship can be safely ignored during the estimation of the specified individual choice models because the impact of a single individual's choice on total traffic flow is negligible. Therefore, each individual will view traffic flow as exogenous to the route and departure time choice process.

MODEL APPLICATIONS

The greatest potential application of the route/departure time choice modeling system is in the context of user equilibrium traffic assignment. The modeling system offers the potential to evaluate the traffic-related impacts of a wide range of policy options related to physical changes in the highway system. In addition, due to the behavioral nature of the models, the impacts of shifts in population demographics can also be assessed.

Unfortunately the model structure does not readily lend itself to equilibrium solutions. All three models (route, travel time, and delay cushion) include vehicle volumes as explanatory variables either in expected travel time terms or directly. Although volumes can be considered exogenous when estimating individual choice models as previously discussed, they must be considered endogenous in the context of a user equilibrium. This endogenicity produces a more complex problem than standard route choice equilibriums, such as stochastic user equilibrium *(17)*, due to the presence of travel time and delay cushion models. Equilibrium with such a group of models is technically possible *(18)* but is beyond the scope of this paper.

SUMMARY AND CONCLUSIONS

Most previous work on route and departure time choice has viewed departure time as a discrete variable. In this paper a route and departure time choice modeling system is developed that treats departure time as a continuous variable. The models were estimated with a sample of work trip commuters and the resulting coefficient estimates were of plausible sign and reasonable statistical significance.

The findings of this study give rise to a number of important points. First, the prospects for continuing advances in development of behavioral route and departure time choice models are most promising. Such models offer the potential for significantly expanding understanding of this critical decision-making process. The second point relates to the importance of proper econometric specification in the estimation of discrete/continuous route and departure time choice models. The estimation results (Tables 3 and 5) suggest that the potential for selectivity bias is considerable. Finally, from the perspective of applications, it is important that future work be directed towards incorporating route and departure time choice models such as those estimated in this paper into a user equilibrium framework. Only then can the true value of such a modeling approach be realized.

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