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.

C.-C. Tong and H. S. Mahmassani, Department of Civil Engineering, University of Texas at Austin, Austin, Tex. 78712. G.-L. Chang, Department of Civil Engineering, University of Utah, Salt Lake City, Utah 84112.

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

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.

$TR_{i,t-2}$ 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.

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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REFERENCES

1. J. L. Horowitz. Travel Demand Analysis: State of the Art and Research Opportunities. *Transportation Research A*, Vol. 19A, 1985, pp. 441–453.
2. H. J. Einhorn and R. M. Hogarth. Behavioral Decision Theory: Processes of Judgement and Choice. *Annual Review of Psychology*, Vol. 32, 1981, pp. 53–88.
3. C. Hendrickson and G. Kocur. Schedule Delay and Departure Time Decisions in a Deterministic Model. *Transportation Science*, Vol. 15, 1981, pp. 62–77.
4. A. de Palma, M. Ben-Akiva, C. Lefevre, and N. Litinas. Stochastic Equilibrium Model of Peak-Period Traffic Congestion. *Transportation Science*, Vol. 17, 1983, pp. 430–453.
5. H. Mahmassani and R. Herman. Dynamic User Equilibrium Departure Time and Route Choice on Idealized Traffic Arterials. *Transportation Science*, Vol. 18, 1984, pp. 362–384.
6. H. S. Mahmassani and G.-L. Chang. Experiments with Departure Time Choice Dynamics of Urban Commuters. *Transportation Research B*, Vol. 20B, No. 4, 1986, pp. 297–320.
7. H. S. Mahmassani, G.-L. Chang, and R. Herman. Individual Decisions and Collective Effects in a Simulated Traffic System. *Transportation Science*, Vol. 20, No. 4, 1986.
8. H. S. Mahmassani and G.-L. Chang. Dynamic Aspects of Departure Time Choice Behavior in a Commuting System: Theoretical Framework and Experimental Analysis. In *Transportation Research Record 1037*, TRB, National Research Council, Washington, D.C., 1985, pp. 88–101.
9. H. S. Mahmassani and R. Herman. Interaction of Trip Decisions and Traffic Systems Dynamics. *European Journal of Operational Research*, Vol. 30, No. 3, 1987, pp. 304–317.
10. H. S. Mahmassani and C.-C. Tong. Availability of Information and Dynamics of Departure Time Choice: Experimental Investigation. In *Transportation Research Record 1085*, TRB, National Research Council, Washington, D.C., 1986, pp. 33–47.
11. G.-L. Chang. Departure Time Choice Dynamics in Urban Transportation Networks. Ph.D. dissertation. Department of Civil Engineering, University of Texas at Austin, Austin, Tex., 1985.
12. A. S. Alfa and D. L. Minh. A Stochastic Model for the Temporal Distribution of Traffic Demand—The Peak Hour Problem. *Transportation Science*, Vol. 13, 1979, pp. 315–324.
13. M. Ben-Akiva, A. de Palma, and P. Kanaroglou. Analysis of Peak-Period Traffic Congestion with Elastic Demand. *Transportation Science*, Vol. 21, No. 3, 1986.
14. M. Ben-Akiva, A. de Palma, and P. Kanaroglou. Effects of Capacity Constraints on Peak-Period Traffic Congestion. In *Transportation Research Record 1085*, TRB, National Research Council, Washington, D.C., 1986, pp. 16–26.
15. J. Horowitz. The Stability of Stochastic User Equilibrium in a Two-Link Network. *Transportation Research B*, Vol. 18B, No. 1, 1984.
16. G.-L. Chang and H. S. Mahmassani. Travel Time Prediction and Departure Time Adjustment Behavior Dynamics in a Congested Traffic System. *Transportation Research B* (in press).
17. G.-L. Chang, H. S. Mahmassani, and R. Herman. A Macroparticle Traffic Simulation Model to Investigate Peak-Period Commuter Decision Dynamics. In *Transportation Research Record 1005*, TRB, National Research Council, Washington, D.C., 1985, pp. 107–120.
18. R. W. Parks. Efficient Estimation of a System of Regression Equations when Disturbances are Both Serially and Contemporaneously Correlated. *Journal of the American Statistical Association*, Vol. 62, 1967, pp. 209–309.
19. D. J. Drummond and A. R. Gallant. *TSCREG—A SAS Procedure for Analysis of Time-Series Cross-Section Data.* SAS Technical Report 5106. SAS Institute, Raleigh, N.C., 1979.
20. H. Theil. *Applied Economic Forecasting*. North-Holland, New York, 1966, pp. 26–36.
21. G. C. Chow. Tests of Equality Between Sets of Coefficients in Two Linear Regressions. *Econometrica*, Vol. 28, 1960, pp. 591–605.
22. J. Neter and W. Wasserman. *Applied Linear Statistical Models.* Irwin, Homewood, Ill., 1974.
23. M. Ben-Akiva and S. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand.* Massachusetts Institute of Technology Press, Cambridge, 1986.