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Contents

Evidence on Impacts of Manufacturer Sourcing on Vehicle Demand

FRED L. MANNERING AND GRACE O. CHU TE

Vehicle manufacturers have been increasingly internationalizing their operations by sourcing their manufacturing processes in different countries. This research seeks to assess the effects that such sourcing decisions will have on consumer vehicle preferences. To do so, a small sample of households was asked to choose among hypothetical sets of vehicles and, from this data, probabilistic choice models were estimated for each household. The estimation results furnished interesting information on consumer sourcing preferences and provide support for the use of a methodological approach in future sourcing studies based on large national data samples.

During the past few years the U.S. automobile market has undergone a number of dramatic and far-reaching transformations. Most of these were induced by the dismal sales years of the early 1980s and the corresponding industrial and governmental responses. Arguably, the most significant of these transformations has been the change in the sourcing of vehicle manufacture. Increasingly, domestic manufacturers have imported vehicles and sold them under popular domestic nameplates, and foreign firms have shifted production to U.S.-based plants. The domestic response apparently results from the comparative cost advantage of foreign manufacture, whereas, in contrast, the response of foreign firms appears to be an effort to expand market shares in light of mandated import restrictions. In any event, it is clear that sourcing decisions will ultimately have a profound impact on the profitability of the automobile industry, domestic employment, and governmental policy.

Perhaps the most important concern in evaluating possible sourcing impacts is the response of U.S. automobile consumers. It is expected, all else being equal, that consumers will have some residual preferences for certain vehicle brands (e.g., Ford, Toyota) or the source of vehicle manufacture (e.g., foreign or domestic), or both. These preferences are likely to be a manifestation of past vehicle experiences, vehicle advertising, nationalistic sentiment, or a combination of these. A number of recent econometric studies on automobile demand have confirmed that the source of vehicle manufacture (domestic or foreign) has a significant effect on consumer preferences *(1–4)*. Although the findings of these studies have been useful in suggesting the presence of sourcing effects, they have been unable to provide detailed expositions of the relationship between sourcing and vehicle demand. This inability is largely the result of the methodology adopted for past studies. Specifically, most previous work has been based on standard revealed preference modeling with the assumption that consumer tastes (i.e., preferences for vehicle attributes and manufacturer sourcing) are constant across the sample populations. In the current study, automobile consumers are presented with hypothetical choices and allowance is made for complete variation of tastes. This approach will make possible a detailed assessment of the relationship between manufacturer sourcing and vehicle demand. Consequently, the results of this study should provide valuable insight into the consequences of manufacturer sourcing decisions.

ECONOMETRIC METHODS

It is assumed that individual households exhibit utility-maximizing behavior in their choice of new vehicles. The utility function will be specified to include five vehicle attributes: purchase price, seating capacity, operating cost, reliability, and sourcing indicators. These attributes were selected on the basis of findings in previous studies *(5)*, and, as will be shown, the present study is structured such that other attributes that affect vehicle demand can be safely excluded.

Therefore the indirect utility provided by vehicle alternative i is formally specified as

$$U = \alpha\, MS + \beta_1 P + \beta_2 SC + \beta_3 OPCOST + \beta_4 REL \qquad (1)$$

where

U = the indirect utility provided by the vehicle alternative;
MS = a vector of manufacturer sourcing indicators;
P = vehicle purchase price in dollars;
SC = seating capacity in adult equivalents;
$OPCOST$ = vehicle operating costs in cents per mile (prevailing fuel price assumed to be \$1.17 per gallon);
REL = Consumer Report's reliability index scaled from 1 to 5, with 5 being most reliable;
α = a vector of parameter unique to each household; and
β's = parameters unique to each household.

In this case, the *MS* vector will reveal preferences for manufacturer sourcing. Specifically, this vector will be structured to include up to four indicator (dummy) variables: foreign brand–foreign made (e.g., Toyota Corolla), foreign brand–domestic made (e.g., Honda Accord), domestic brand–foreign made (e.g., Dodge Colt), and domestic brand–domestic made (e.g., Ford Thunderbird). Estimation information related to the signs, magnitudes, and significance levels of these variables will identify consumer preferences for manufacturer sourcing.

The other attributes in Equation 1 are also presumed to be important determinants of the vehicle selection process. A priori, it is expected that purchase price and operating costs will have a negative effect on vehicle preference and that seating capacity and reliability will have a positive influence.

To econometrically estimate Equation 1, a random component is added to arrive at the random utility expression:

$$V = U + \varepsilon \qquad (2)$$

In traditional discrete choice econometric analysis, random util-

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ities are estimated over an entire sample of households thereby obtaining a single average utility expression. One key factor used in justifying this randomness is that the tastes of individual decision makers vary in an unobserved manner. The present case differs from the traditional approach in that utility expressions are estimated for each individual household, which explicitly accounts for possible differences in tastes of households. However, there is still support for randomness due to tastes because studies have demonstrated *(6, 7)* that an individual's tastes tend to fluctuate from one discrete choice to another. In this sense, the application of probabilistic analysis to model individual decisions is justified on traditional grounds.

Given acceptance of the randomness of individual decisions, an appropriate probability distribution can be selected. As is well documented *(8)*, the choice of the distribution of ε (in Equation 2) can be used to derive a wide range of estimable probabilistic choice models. For computational convenience, it is assumed that ε is generalized extreme value distributed, thus giving the standard multinomial logit form, which is readily estimable by maximum likelihood techniques,

$$P_i = e^{U_i} / \sum_j e^{U_j} \tag{3}$$

where P_i is the probability of the household selecting vehicle i and U_i is the indirect utility of alternative i as defined in Equation 1.

The use of logit models in automobile demand research is described elsewhere *(5, 9)*. However, unlike most previous studies, which have relied on data from revealed preferences, this study will construct hypothetical choice situations to ensure that a sufficient amount of data is available to estimate logit models for each household surveyed. Two earlier automobile demand studies used hypothetical choice data with encouraging results *(7, 10)*. Both of these studies sought to determine the potential demand for electric vehicles and for this reason did not consider possible sourcing preference.

Hypothetical choice sets afford the researchers two important advantages. First, preferences for vehicles not currently offered in the marketplace can be assessed. This is particularly important to the present work because the researchers are not constrained by the historically limited use of manufacturer sourcing. The second advantage is that the researcher can ensure that the constructed choice sets exhibit sufficient variation to allow precise parameter estimation. The primary disadvantage of such data is that the decision maker's response may differ from the one he would have made if faced with a real choice situation. It is believed, however, that well-constructed choice sets and a survey that properly instructs respondents can mitigate any potential problem of this kind.

DATA COLLECTION AND DESCRIPTION

Data were collected from 21 households in the State College, Pennsylvania, metropolitan area. The selection of households was undertaken to ensure that five ownership classifications were properly represented. These classifications include households currently owning (*a*) one domestic vehicle, (*b*) one foreign vehicle, (*c*) two domestic vehicles, (*d*) two foreign vehicles, or (*e*) one domestic and one foreign vehicle. In this case all classifications refer to vehicles with the same source and brand origins (e.g., a foreign vehicle is defined as foreign made–foreign brand). This categorization of households reflects the expectation that vehicles currently owned will strongly affect preferences regarding future vehicle acquisitions. As will be shown, this expectation is borne out in the subsequent empirical findings.

The household survey form (copies of which are available from the authors on request) began with a set of instructions detailing the conditions and assumptions under which households were to make their decisions about the purchase of a new, current-model-year vehicle. This was followed by a number of queries relating to socioeconomic conditions and previous vehicle ownership. Such information was collected for its potential usefulness in interpreting estimation results. Table 1 gives a summary of these data categorized by ownership classification.

The core of the survey consisted of 30 hypothetical choice situations. A typical example of one of these is given in Table 2. These choice sets were carefully constructed to be as realistic as possible and to allow for maximum attribute variation. All households surveyed were presented with the same 30 choice sets that consisted of four vehicles defined by manufacturer sourcing combinations. Finally, the survey concluded with a debriefer that contained questions about the subject's attitude, choice-making strategies, and general impressions of the survey approach. Again, as with socioeconomic data, this information has potential value in assessing empirical findings.

In general, the survey was well received. Most respondents found it to be an enjoyable exercise, and they indicated a logical decision-making process that led them to their vehicle selections. In most cases these selections were governed by socioeconomic conditions (e.g., income, household size), but established preferences for location of manufacture and vehicle brand were acknowledged by many of the respondents as a significant factor.

MODEL ESTIMATION

To evaluate the impacts of manufacturer sourcing, three model specifications were estimated for each household in the sample.

TABLE 1 SUMMARY OF PARTICIPANT CHARACTERISTICS (averages unless otherwise noted)

					Percentage That Ever Owned	
Ownership Classification	No. of Participants	Annual Income ($)	Participant Age (yr)	No. of Household Members	Foreign Brand	Domestic Brand
One domestic	5	26,100	30.8	1.8	20	100
One foreign	4	20,625	31.5	2.5	100	25
Two domestic	5	41,100	41.6	3.2	40	100
Two foreign	3	39,000	50.0	3.3	100	100
One domestic and one foreign	4	39,625	42.0	3.3	100	100
Total (average)	21	(33,048)	(38.4)	(2.8)	(76)	(86)

TABLE 2 TYPICAL VEHICLE CHOICE SET

	Type			
Attribute	U.S. Made–Foreign Brand	Foreign Made–U.S. Brand	Foreign Made–Foreign Brand	U.S. Made–U.S. Brand
Cost ($)	10,000	8,700	6,400	9,500
Capacity (adult equivalents)	4	4	5	5
Fuel efficiency (mpg)	29	36	32	23
Reliability (Consumer Report's index)	4	5	3	2

The first included a variable to indicate the source of vehicle manufacture. This variable was defined as one if the vehicle was manufactured in the United States and as zero otherwise. Hence, this specification accounts for preferences for vehicle origins with no explicit regard for preferences between foreign and domestic brands. In contrast, the second specification explicitly considers different preferences for foreign and domestic brands without regard to the vehicle's place of manufacture. This specification includes a variable defined as one if the vehicle is a domestic brand and as zero otherwise. The third and final model specification is "fully specified" in that it accounts for all origins of manufacture and brand combinations. This was achieved by including indicator variables for (*a*) domestic made–domestic brand, (*b*) domestic made–foreign brand, (*c*) foreign made–domestic brand, and (*d*) foreign made–foreign brand.

Ideally, the fully specified model would be preferred to the other two specifications simply because much more information can be provided by the additional indicator variables. However, the fully specified model proved difficult to estimate, and in many cases convergence of the maximum likelihood estimation algorithm was not achieved. The result was highly unreliable parameter estimates. It is possible that this convergence problem is a result of attempting to estimate too many parameters (seven in all) with too few observations (only 30 per individual household).

Even though the preferred fully specified form gave disappointing results, the two other specifications can provide potentially useful information about manufacturer sourcing decisions. For example, the model with the origin of manufacture indicator variable captures notions of the relative quality of domestic labor and consumer support for domestic labor, whereas the brand indicator model accounts for relative factors such as corporate quality control, parts and repair availability, and so on. Clearly, understanding consumer preferences of these types is an important vehicle-marketing concern.

The actual parameter estimation results for the domestic-origin and domestic-brand models are given, by ownership classification, in Table 3 (parameter estimates of the fully specified models are available from the author on request). With few exceptions, the parameter estimates related to the vehicle attributes of purchase price, capacity, operating costs, and reliability were of expected sign, and their statistical significance (as indicated by corresponding *t*-statistics) was generally good. In addition, in many cases, there is a substantial difference between the magnitudes of the parameter estimates from household to household. This finding provides support for the decision to use individual logit models (i.e., thereby accounting for taste variations among households) as opposed to a single logit model estimated over the entire household population.

Although the preferences for the vehicle attributes discussed previously are important, the concern is with manufacturer sourcing indicator variables. Findings in this regard are described in detail in the next section.

ASSESSMENT OF HOUSEHOLD SOURCING PREFERENCES

To evaluate the significance of the sourcing indicator variables, the results of the three models discussed earlier (i.e., origin indicator model, brand indicator model, and fully specified model) are compared with a model that constrains the values of all indicators to be zero (i.e., includes parameter estimates of only price, capacity, operating cost, and reliability attributes). Statistically, this comparison is achieved by using the likelihood ratio test, defined as

$$-2\,[L^*(\beta r) - L^*\,(\beta u)]$$

where $L^*(\beta r)$ is the log-likelihood at convergence for the constrained model (i.e., all indicator parameters equal to zero) and $L^*(\beta u)$ is the log-likelihood at convergence for the indicator variable model being tested (one of the three specifications discussed earlier).

Under the null hypothesis that the restricted and unrestricted models are equal, this likelihood ratio statistic is χ^2 distributed. For the case of the origin and brand indicator models, the statistic has 1 degree of freedom (5 – 4), and it has three degrees of freedom for the fully specified model (7 – 4). Table 4 gives the results of the application of the likelihood ratio test. The values in this table give the percent confidence with which the hypothesis of equality between the restricted and the unrestricted model can be rejected (i.e., indicating that origin and brand preferences are significant). In addition, for origin and brand indicator models, preferences for domestic or foreign concerns are noted.

The results for households that currently own one domestic vehicle indicate that all five respondents have preferences for vehicles of domestic origin. In four of these cases the statistical significance of the preferences is rather high, as indicated by the confidence levels in Table 4. Four of the five respondents exhibit preferences for domestic brands, but these are generally less significant statistically than their origin preferences. Note that Respondent 2 has highly significant preferences for vehicles of domestic origin along with preferences for foreign brands. This dichotomy was found to exist in a number of model estimations. An analysis of the fully specified models of these households suggests a strong preference for domestic made–foreign brand vehicles, which explains the results of the single indicator variable models. Finally, three of the five fully specified models achieved

TABLE 3 ESTIMATION RESULTS FOR MODELS WITH SOURCE INDICATORS AND MODELS WITH BRAND INDICATORS (*t*-statistics in parentheses)

Ownership Classification	Participant No.	Purchase Price ($)	Capacity (persons)	Operating Costs (cents/mi)	Consumer Report's Reliability	Domestic Origin Indicator	Domestic Brand Indicator
One domestic	1	−.0002	0.448	−1.01	1.13	0.23	–
		(−1.1)	(2.0)	(−3.1)	(2.4)	(0.3)	–
		−.0002	0.431	−1.01	1.04	–	0.085
		(−1.1)	(1.9)	(−3.0)	(2.9)	–	(0.2)
	2	−.0011	0.361	−1.41	4.69	3.77	–
		(−2.9)	(1.2)	(−2.7)	(3.6)	(2.7)	–
		−.0005	0.527	−7.7	2.47	–	−0.975
		(−1.8)	(1.9)	(−2.1)	(3.5)	–	(−1.7)
	3	−.0003	0.086	−0.35	0.24	1.12	–
		(−1.6)	(0.5)	(−1.5)	(0.6)	(1.8)	–
		−.0002	0.013	−0.34	−0.18	–	0.739
		(−1.0)	(0.1)	(−1.5)	(−0.7)	–	(1.7)
	4	−.0004	0.441	−1.26	1.04	0.82	–
		(−1.9)	(2.0)	(−3.3)	(2.2)	(1.2)	–
		−.0003	0.423	−1.26	0.67	–	0.287
		(−1.6)	(1.9)	(−3.2)	(2.2)	–	(0.6)
	5	−.0003	−0.033	−0.02	3.61	1.62	–
		(−1.0)	(−0.1)	(−0.1)	(3.3)	(1.5)	–
		−.0001	−0.008	0.30	2.87	–	0.354
		(−0.3)	(−0.1)	(0.9)	(3.5)	–	(0.6)
One foreign	1	−.0017	0.251	−0.89	1.80	0.11	–
		(−4.0)	(0.9)	(−2.4)	(3.0)	(0.1)	–
		−.0017	0.247	−0.90	1.79	–	0.123
		(−3.9)	(0.9)	(−2.3)	(3.6)	–	(0.2)
	2	−.0013	1.28	−1.38	2.06	0.62	–
		(3.2)	(3.1)	(−2.9)	(3.3)	(0.8)	–
		−.0011	1.30	−1.32	1.75	–	−0.42
		(−3.0)	(3.2)	(−2.8)	(3.4)	–	(−0.8)
	3	−.0006	0.06	−1.28	1.1	−0.19	–
		(−2.4)	(0.3)	(−3.3)	(2.3)	(−0.3)	–
		−.0007	−0.0007	−1.42	1.32	–	0.63
		(−3.0)	(−0.1)	(−3.2)	(3.5)	–	(1.2)
	4	−.0006	−0.69	−1.21	1.88	−0.91	–
		(−3.0)	(−0.1)	(−3.2)	(3.5)	(−1.2)	–
		−.0007	0.84	−1.27	2.19	–	−0.88
		(−2.5)	(2.7)	(−2.7)	(3.3)	–	(−2.6)
Two domestic	1	.0001	4.05	−5.64	3.2	1.65	–
		(0.3)	(2.4)	(−2.3)	(1.8)	(1.2)	–
		.0007	4.31	−4.13	1.61	–	−1.98
		(1.3)	(2.1)	(−2.4)	(1.6)	–	(−2.4)
	2	−.0001	0.15	−0.09	0.46	0.59	–
		(−0.3)	(0.8)	(−0.4)	(1.3)	(1.0)	–
		−.00002	0.01	−0.07	0.39	–	1.33
		(−0.1)	(0.1)	(−0.3)	(1.5)	–	(2.9)
	3	−.00001	1.65	−0.52	−1.1	4.52	–
		(−0.01)	(2.8)	(−1.5)	(−1.6)	(2.9)	–
		.0004	0.91	−0.34	−1.92	–	0.75
		(1.9)	(2.6)	(−1.2)	(−3.8)	–	(1.4)
	4	−.0001	0.51	−2.34	0.81	0.04	–
		(−0.6)	(1.9)	(−3.4)	(1.6)	(0.1)	–
		−.0001	0.54	−2.35	0.73	–	−0.57
		(−0.4)	(2.0)	(−3.4)	(2.0)	–	(−1.1)
	5	.0002	0.31	−0.13	0.10	1.31	–
		(0.7)	(1.5)	(−0.6)	(0.2)	(2.0)	–
		.0003	0.14	−0.08	−0.35	–	1.51
		(1.7)	(0.7)	(−0.3)	(−1.3)	–	(3.0)
Two foreign	1	.0005	1.07	−3.62	8.61	1.13	–
		(1.1)	(2.1)	(−1.8)	(1.9)	(0.9)	–
		.0004	1.00	−3.06	7.38	–	0.22
		(1.0)	(2.2)	(−1.8)	(2.0)	–	(0.3)
	2[a]	−.0005	0.41	−0.26	1.55	0.42	–
		(−2.2)	(2.0)	(−1.0)	(3.2)	(0.6)	–
	3	−.0004	0.14	−1.31	1.46	0.05	–
		(−1.9)	(0.7)	(−0.5)	(3.1)	(0.1)	–
		−.0004	0.87	−0.07	1.61	–	−4.24
		(−1.3)	(2.4)	(−0.2)	(2.9)	–	(−3.6)

TABLE 3 ***continued***

Ownership Classification	Participant No.	Purchase Price ($)	Capacity (persons)	Operating Costs (cents/mi)	Consumer Report's Reliability	Domestic Origin Indicator	Domestic Brand Indicator
One domestic and one foreign	1	–.0005	0.50	–.79	0.73	–0.54	–
		(–2.2)	(2.2)	(–2.6)	(1.8)	(–0.8)	–
		–.0006	0.51	–0.79	0.95	–	–0.10
		(–2.7)	(2.2)	(–2.6)	(3.0)	–	(–0.2)
	2	–.0003	0.73	–1.24	3.90	2.51	–
		(–1.0)	(2.2)	(–2.2)	(3.3)	(2.0)	–
		–.0002	0.61	–0.66	2.41	–	0.07
		(–0.1)	(2.3)	(–1.6)	(3.6)	–	(0.1)
	3	–.0009	0.59	–0.99	0.99	0.28	–
		(–3.3)	(2.4)	(–3.1)	(2.2)	(0.4)	–
		–.0008	0.66	–0.95	0.79	–	–0.73
		(–3.3)	(2.6)	(–2.9)	(2.5)	–	(–1.5)
	4	–.0012	1.26	–1.72	1.58	0.28	–
		(–3.0)	(3.2)	(–3.3)	(2.7)	(0.4)	–
		–.0011	1.38	–1.70	1.43	–	–1.05
		(–2.9)	(3.3)	(–3.0)	(2.9)	–	(–1.7)

Note: Dashes = not applicable.

[a]Brand indicator model did not converge.

convergence, and their resulting parameter estimates reinforce the general preference for vehicles of domestic origin and brand.

The findings for households that own one foreign vehicle were mixed with regard to brand and origin preference. Half of the respondents preferred domestic origins and brands, and half preferred foreign. However, the preferences of these households were, for the most part, statistically insignificant. It can be speculated that this relative ambivalence toward manufacturer sourcing may be due to income restraints. This is based on the observation that the subjects in this ownership classification had the lowest income levels (Table 1) and, in the survey debriefer, most mentioned vehicle price as an important factor governing their decision-making process.

Households that own two domestic vehicles all exhibited preferences for vehicles of domestic origin, most at reasonable levels of statistical significance. However, preferences for vehicle brands were mixed, with three respondents preferring domestic and two preferring foreign. The findings here suggest, as discussed earlier, the preference of some households for domestic made–foreign brand vehicles. This may indicate a general confidence in corpo-

TABLE 4 PERCENT CONFIDENCE AT WHICH THE HYPOTHESIS OF EQUALITY CAN BE REJECTED BETWEEN MODELS WITH AND WITHOUT INDICATOR VARIABLES

		Origin Indicator		Brand Indicator		
Ownership Classification	Participant No.	Positive Domestic	Positive Foreign	Positive Domestic	Positive Foreign	Fully Specified
One domestic	1	25	NA	16	NA	–[a]
	2	99	NA	NA	93	99
	3	94	NA	93	NA	–[a]
	4	78	NA	47	NA	53
	5	90	NA	47	NA	93
One foreign	1	16	NA	16	NA	1
	2	60	NA	NA	60	43
	3	NA	19	78	NA	59
	4	NA	78	NA	98	54
Two domestic	1	79	NA	NA	98	–[a]
	2	71	NA	99	NA	–[a]
	3	99	NA	87	NA	–[a]
	4	8	NA	NA	73	99
	5	97	NA	99	NA	–[a]
Two foreign	1	68	NA	25	NA	22
	2	47	NA	–[a]	–[a]	–[a]
	3	8	NA	NA	99	–[a]
One domestic and one foreign	1	NA	60	NA	16	39
	2	99	NA	8	NA	90
	3	35	NA	NA	87	54
	4	35	NA	NA	93	84

Note: NA = not applicable.

[a]Convergence of maximum likelihood not achieved.

rate manufacturing processes and quality control, an area in which foreign firms (particularly Japanese firms) are perceived to have a considerable advantage.

All three of the households that own two foreign vehicles demonstrated preferences for domestic origins, but these were not statistically significant. Two of the three brand indicator models converged and one of these gave statistically significant results, a preference for foreign-brand vehicles. The only fully specified model to converge produced statistically inconclusive results.

Finally, three of the four households that own one domestic and one foreign vehicle indicated a preference for domestic origins (one of these at a high level of significance). Conversely, three of four households were found to prefer foreign brands (two of these indicate significant preferences). All of the fully specified models converged and two households exhibited statistically well-defined preferences in regard to origin and brand combinations.

GENERAL FINDINGS

On the basis of the estimation results of this study, a number of inferences can be drawn about manufacturer sourcing. First, in the sample, neither the origin of manufacture nor the vehicle brand prove to be particularly dominant in the majority of cases (see confidence levels in Table 4). Although some households consider sourcing concerns to be important, clearly many were responding primarily to other vehicle attributes (price, capacity, fuel efficiency, reliability). Indeed, a number of respondents indicated in the survey debriefer that they completely ignored origin and brand concerns. In some respects this finding is surprising because it was initially expected that American consumers would exhibit strong sourcing preferences due to the historic domination of the American market by domestic firms. That strong preferences were not found consistently across the sample may reflect the internationalization of at least some segments of the U.S. automobile market. If this is the case, it is welcome news to domestic firms that are planning increases in foreign sourcing.

The second point relates to that portion of the household population that does exhibit strong sourcing preferences. As the data in Table 4 indicate, most of these preferences favor vehicles manufactured in the United States (this is also indicated in the coefficient estimates of the fully specified model). This suggests that the manufacture of foreign brands in the United States is likely to have an adverse effect on the market shares of domestic firms. This is particularly true when coupled with the strong preferences for foreign brands that were indicated by a number of respondents. Potential problems caused by this phenomenon can be attributed, in large part, to the Japanese import restrictions that have encouraged a shift in Japanese production to sites within the United States.

The final point relates to the sourcing preferences of households that currently own foreign vehicles. In most cases, these households do not appear to have developed strong loyalties to the origin or brand of the vehicles they own. Indeed, most owners of foreign vehicles still reveal some preference for vehicles of domestic origin. This is welcome news to domestic firms in that it suggests that market shares lost to foreign manufacturers in recent years can be recaptured without having to overcome established vehicle loyalties.

It is important to qualify the findings of this study by mentioning a few important concerns. First, due to the small sample size, this study must be viewed as exploratory. Although the findings are suggestive, a national sample of several hundred households is needed to make definitive statements regarding household sourcing preferences. The second concern relates to forecasting and the determination of aggregate demand from individual probabilistic choice models. Again, the size of the sample precludes performing any work in this area. It should be noted, however, that aggregation and forecasting with individual probabilistic choice models have been successfully demonstrated in other research efforts *(7)*. Finally, there is the issue of relating demographic factors to individual preferences. The authors were generally unable to isolate any strong effects of this kind. In future work a larger sample size would enable the researcher to obtain meaningful statistical inferences relating demography and individual preferences.

SUMMARY AND CONCLUSIONS

The objective of this paper was to provide evidence on the effects that manufacturer sourcing has on automobile demand. To achieve this, 21 households were interviewed and asked to choose among hypothetical sets of vehicles. Then, for each household, probabilistic choice models were estimated and the resulting coefficients were used as a basis for evaluating preferences for manufacturer sourcing.

The findings indicate that the vehicle-purchasing population consists of some households with few or no sourcing preferences and others with rather strong preferences. For those with minimal preferences, U.S. corporate strategies aimed at more foreign sourcing will have little effect on vehicle demand. For those households with strong preferences (which overwhelmingly support domestic manufacture), results suggest that the strategy of foreign firms locating plants in the United States will improve their market position. Finally, it is noted that preferences for foreign origins and brands are not well established among current foreign car owners, which raises the possibility that domestic firms may still recapture lost market shares.

From a methodological standpoint, the use of individual probabilistic choice models based on hypothetical choice situations proved effective. The ability of the approach to allow for complete variation in tastes among households was essential, as is evidenced by the wide variability of parameter estimates from one household to another. This is particularly true for the sourcing indicator variables (Table 3). It is therefore concluded that similar methodological approaches should be used in future manufacturer sourcing studies.

REFERENCES

1. K. Train. *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand.* Massachusetts Institute of Technology Press, Cambridge, 1986.
2. J. Berkovec and J. Rust. A Nested Logit Model of Automobile Holdings for One Vehicle Households. *Transportation Research*, Vol. 19B, No. 4, 1985.
3. F. Mannering and H. Mahmassani. Consumer Valuation of Foreign and Domestic Vehicle Attributes: Econometric Analysis and Implications for Auto Demand. *Transportation Research*, Vol. 19A, No. 3, 1985.
4. F. Mannering and C. Winston. A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization. *Rand Journal of Economics*, Summer 1985.
5. D. Hensher. Empirical Vehicle Choice and Usage Models in the Household Sector: A Review. *International Journal of Transport Economics*, Vol. 12, No. 3, 1985, pp. 231–259.

6. A. Tversky. Intransitivity of Preferences. *Psychological Review*, Vol. 76, 1969, pp. 31–48.
7. J. Calfee. Estimating the Demand for Electric Automobiles Using Fully Disaggregated Probabilistic Choice Analysis. *Transportation Research*, Vol. 19B, No. 4, 1985.
8. D. McFadden. "Econometric Models of Probabilistic Choice." In *Structural Analysis of Discrete Data with Econometric Applications* (C. Maski and D. McFadden, eds.), Massachusetts Institute of Technology Press, Cambridge, 1981.
9. F. Mannering and K. Train. Recent Directions in Automobile Demand Modeling. *Transportation Research*, Vol. 19B, No. 4, 1985.
10. S. Beggs, N. Cardell, and J. Hausman. Assessing the Potential Demand for Electric Cars. *Journal of Econometrics*, Vol. 17, 1981, pp. 1–19.

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Bicyclist Link Evaluation: A Stated-Preference Approach

K. W. AXHAUSEN AND R. L. SMITH, JR.

The purpose of this study is to develop a methodology for evaluating bicycle route choice and to test the individual link preference component of the methodology. The focus is on the relationships between the qualitative factors that describe an individual link of a bicycle route and the overall evaluation of that route. It is demonstrated that it is possible to use functional measurement to estimate one of the partial utility functions of the hypothesized overall utility function of route choice. The utility of the individual links is estimated as a function of six link attributes. All but one of the attributes have significant main effects at the 5 percent level of confidence.

During the last 10 years transportation planners and engineers have rediscovered the bicycle as a mode of transportation. This rediscovery has been caused by a number of factors. Probably the single most important factor was the energy crisis of 1973–1974 and the following boom in bicycle sales. In addition, the environmental movement sharpened the awareness of the need for energy-efficient and pollution-free solutions to transportation problems. Increased health awareness was a third factor in the promotion of the bicycle. Changes in professional attitude are illustrated by the inclusion of bicycles in traffic counts and travel surveys. What was once viewed as a children's toy is now viewed as a legimate mode of transportation.

Most research and planning efforts in recent years have been concentrated on solving the practical problems of the increased number of bicycle accidents and the design of bicycle facilities. Many cities built new bike paths, signed new bike lanes, and marked new bike routes in addition to rehabilitating old facilities. Still, many expectations for the new facilities were not fulfilled because the facilities did not fit the needs of the intended user groups.

This disappointment resulted in part from a lack of understanding of bicyclists and their route choice. Not much effort was spent studying the behavior of bicyclists and the factors that influence route choice. Only accidents involving bicyclists have been studied extensively during the last decade.

As is the case with automobile drivers, there is little knowledge of bicyclists' trade-offs between travel time and travel costs and qualitative factors such as bicycle facilities or surface quality. Qualitative factors have an obvious role in the route choice of bicyclists, who are more exposed to environmental influence than are car drivers. Research on the attitudinal factors of automobile driver route choice *(1, 2)* showed that qualitative factors also influence them.

There are two basic approaches to estimating such trade-offs. The estimates can be performed on revealed-preference data on actual route choices or on stated-preference data from the results of a controlled experiment (simulation of choice). Given the problems inherent in collecting the qualitative and quantitative data on the bicycle networks required for the first approach, only the second approach was feasible within the constraints of this study.

In recent years a number of methods have been developed for collecting and analyzing revealed-preference data. The most prominent methods are conjoint analysis and functional measurement. On the basis of a review of the relevant literature, it was decided to employ the technique of functional measurement, which has been developed by Anderson *(3)* and Louviere et al. *(4)*. [An introduction to functional measurement is given in Kocur et al. *(5)*.] The primary advantages of functional measurement are the ease of data analysis and the availability of good statistical tests of significance of the model parameters.

The purpose of this study is to develop a methodology for evaluating bicycle route choice and to test the individual link preference component of the methodology. The focus of the study is on the relationships between the qualitative factors that describe an individual link of a bicycle route and the overall evaluation of that link. Following a short literature review, the approach and the aims of the study are explained in more detail and the design of the survey is outlined. The analysis of the survey is divided into two

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parts. In the first part the respondents are described in terms of their socioeconomic characteristics. The analysis of the relationships between the qualitative factors and the overall evaluation of the link is presented in the second part. An attempt is also made to segment the link preference function by socioeconomic characteristics.

LITERATURE REVIEW

Four recent studies are devoted exclusively to the question of the route choice of bicyclists: Upcott *(6)*, Teichgraeber *(7)*, Krause *(8)*, and Bradley and Bovy *(9)*. The work of Teichgraeber and Krause concentrates on bicyclists' sensitivity to avoiding detours and on the general factors that affect route choice. Teichgraeber documents the strong effects intersections can have on the route choice of bicyclists. Upcott applies a shortest path and a stochastic route choice assignment model to the route choice of bicyclists. Both models perform satisfactorily, but it is difficult to generalize the results because the study is based on a survey of high school students in a small English town. Bovy and Bradley's paper is based on a current major study of the route choice of bicyclists in The Netherlands. Using functional measurement, the authors estimate a utility function for the route choice of bicyclists using four factors: length of trip, surface quality, traffic volumes, and bike facilities. The influence of trip length and surface quality is approximately equal and nearly twice as large as the influence of traffic volumes and bike facilities. The authors surveyed only regular bicyclists. The model used by Bovy and Bradley assumes that the levels of the three qualitative variables are constant over the length of the trip and that intersections have no significant influence. More research is needed to determine if these strong assumptions are valid.

In addition, there are a number of studies that focus on the effects of bike lanes and bike paths: Kroll and Ramey *(10)*; Walsh *(11)*; Kroll and Sommer *(12)*; Lott, Tardiff, and Lott *(13)*; and Ambrosius *(14)*. These studies document the increase in subjective safety that most bicyclists experience when using bike lanes and paths. Ambrosius shows the positive influence of a complete bicycle infrastructure on the modal share of the bicycle.

APPROACH AND AIM OF STUDY

The decision process of bicyclists can be formulated in the following form, which has been proposed for other choice problems by Louviere and Meyer *(15)*:

$$X_{ij} \rightarrow x_{ij} \rightarrow U_i \rightarrow R_i \rightarrow C_i$$

where

- X_{ij} = a vector of the j observable characteristics or attributes describing the ith alternative,
- x_{ij} = the vector of the perceived or psychological values of the observable attributes,
- U_i = the vector of the utility of the i alternatives,
- R_i = the vector of stated evaluations of the i alternatives as generated by a laboratory experiment, and
- C_i = the behavioral response to alternative i as observable in the field.

The response could be the choice frequency of, in this case, a route.

The utility of the ith alternative is related to the observable attributes by

$$U_i = F[f_j\,(X_{ij})] \tag{1}$$

Also, the stated response or evaluation (R_i) is related to the utility (U_i) by a simple mathematical transformation:

$$R_i = a + bU_i \tag{2}$$

This assumption allows use of the results of the analysis of the stated-response experiment for the prediction of the C_i's. The behavioral response (C_i) can be predicted from the values of the U_i's depending on the assumptions made about the distribution of the error terms of the U_i's.

The set of attributes or characteristics that are important for bicycle route choice, as found in the literature, includes: (*a*) overall travel time, (*b*) travel time of the individual links and other link attributes, and (*c*) average waiting time at intersections and other intersection attributes. For the purpose of this study it is assumed that it is possible to decompose the overall route attributes (X_{ij}) into individual link and intersection attributes so that

$$X_{ij} = [T_i, (t^n, L^n_{ik}), (w^m, I^m_{il})] \tag{3}$$

where

- T_i = travel time of route i,
- t^n = travel time of link n,
- L^n_{ik} = kth attribute of link n,
- w^m = average wait time at intersection m, and
- I^m_{il} = lth attribute of intersection m.

It is also assumed that it is possible to estimate the utility functions of a partial set of route attributes so that

$$U_i = F[u_1\,(T_i),\, u_2\,(t^n, L^n_{ik}),\, u_3\,(w^n, I^n_{il})] \tag{4}$$

where the u_i's are the partial utility functions.

The aim of this research was to test the usefulness of this approach by developing one of the partial utility functions as a first step toward the development of a route choice model for bicyclists. The partial utility functions are the building blocks of the overall utility functions. The research here is limited to the estimation of the partial utility function of bicyclists' evaluation of the individual links.

Preliminary studies and the literature review show that three basic concepts provide the framework for the evaluation of a route: (*a*) traffic volumes, (*b*) control of movement, and (*c*) comfort of the ride. "Control of movement" describes the wish of the bicyclist to travel safely at the desired speed without too much interference in the form of traffic controls or other traffic. At the link level bicycle facilities are the main variable that describes this concept. "Comfort" relates to the quality of the ride and the quality of the environment. The slope of the link, the surface quality of the link, and the abutting land use were chosen to represent this concept. The last variable needed to complete the description was the length of the link. For each of the six variables—traffic volumes, length, surface quality, slope, land use, and bike facilities—three levels were chosen to span the range of values typically found in urban areas (Table 1).

TABLE 1 VARIABLES OF THE FACTORIAL DESIGN AND THEIR LEVELS

Variable	Level 0	Level 1	Level 2
Length of link (blocks)	2	1	1/2
Slope (%)	6	3	0
Traffic volumes	High	Medium	Low
Abutting land use	Industrial	Residential	Park
Bike facilities	None	Bike lane	Bike path
Surface quality	Low	Medium	High

An experimental design was required that would give an estimate of the relative importance of the six factors and all two-way interactions because it was impossible to exclude certain interactions on the basis of the literature.

DESIGN OF THE SURVEY

The questionnaire consisted of two main parts: the factorial design experiment needed for the estimation of the partial utility function and general socioeconomic questions.

Conner and Zelen *(16)* include an experimental design that met the specifications: a 1/3 3^6 factorial design with nine blocks of 27 questions each. Every respondent would have to evaluate one of the blocks. This blocking requires the assumption that there is no effect associated with the blocks.

The values of the levels were explained or illustrated with local examples in the questionnaire for the variables slope, surface quality, and bike facilities. Preliminary testing had shown that the respondents had very similar conceptions of low, medium, and high traffic volumes. Therefore the levels of the factor "traffic work or university on a 20–point scale with 20 being the most desirable link and zero the least desirable link to ride on.

RESPONDENTS

The survey was distributed to two groups: students of two civil engineering classes and the members of the local bicycle touring club (Bombay Bicycle Club). Neither of the groups is representative of the bicycling public as a whole, but this study did not attempt to be representative. Both groups should, however, be representative of two segments of the bicycling public: university students and older, regular bicyclists. The survey was distributed to the students the third week of February 1984. The principal author explained the survey and remained in the classroom to answer further questions. A total of 124 complete questionnaires were obtained from the students. The questionnaire with a cover letter explaining the purpose of the survey and a stamped return envelope was sent to a systematic sample of one-third of the members of the bicycle club. By the end of the third week following the mailing (third week of February 1984) 69 of the 130 mailed questionnaires had been returned complete.

Table 2 gives a summary of the most important characteristics of the two groups. The members of the bicycle club are older and own more cars, but they use the bicycle more often than do the students for their work or school trips. Both groups use five- or ten-speed bicycles almost exclusively.

TABLE 2 CHARACTERISTICS OF RESPONDENTS

Characteristic	Students[a]	Bicycle Club Members[a]
Average age (yr)	22.0 (0.2)	34.0 (1.2)
Male (%)	82	70
Female (%)	18	30
Own one or more cars (%)	56	88
Own one or more bicycles (%)	92	99
Mode most frequently used for school or work trip during good weather months		
Car (%)	13	22
Bicycle (%)	33	65
Walking (%)	41	6
Average years of bike ownership	11.0 (1.0)	17.0 (1.3)
Average years of regular bike use[b]	5.9 (0.4)	6.2 (0.6)
Self-evaluation of experience as bicyclist[c]		
Average	4.6 (0.1)	5.3 (0.2)
Distribution (%)		
≤ 3	14	11
4,5	60	35
≥ 6	26	54

[a]Standard errors in parenthesis.
[b]Regular use was defined as 10 or more bike trips per week.
[c]Scale of 0 to 7 with 7 as most experienced.

The greater use of the bicycle by bicycle club members is reflected in the self-evaluation of the two groups. The students evaluate their experience as a bicyclist 0.7 points lower than do the members of the bicycle club on a 7–point scale (0 = not at all experienced, 7 = extremely experienced). The use of self-evaluation for the measurement of experience is not completely satisfactory, but for this research it was the best way to estimate this important variable. The self-evaluation is correlated with the length and intensity of bicycle ownership and use, but the correlations are not especially high.

ESTIMATION OF UTILITY FUNCTIONS

Analytical Procedure

Although the size of the blocks was relatively large (27 alternative links), only a small number of students did not complete the tasks and only a very small number of alternatives were not evaluated.

As the data in Table 1 indicate, the variables were coded to produce positive coefficients in the regression analysis. For example, high traffic volumes were coded as zero because it could be assumed that the utility of traffic volumes decreases with increasing traffic volumes.

To assure comparability of the individual responses, the analysis was performed on the normalized responses. For every respondent the mean and standard deviation of the responses were calculated and the responses normalized. In this way it is possible to compare the sensitivity of the respondents to the various variables using a common metric. Comparison of the results for the normalized responses with those for the unnormalized data showed no differences in the conclusions to be drawn from the analysis.

The analysis was carried out in two separate stages for both the student and the bicycle club data sets. In the first stage the significance of the variables (factors) was tested and in the second stage the partial utility function was estimated with linear and piecewise linear multiple regression. Attempts were also made to segment the partial utility function for each data set on the basis of socioeconomic characteristics.

Significance Tests

For the normalized responses the design consists of one random factor—the respondents—and six fixed factors—the design variables. For this case of a repeated-measurement design the correct test of significance of a factor is not the F-ratio of mean square of the factor to mean square of the error but

$$F(Factor) = MS(Factor)/MS(Factor*Respondents).$$

For a large data set, such as the student data set, it is either computationally infeasible or too expensive to test interactions in this way. [In the course of the anaysis one two-way interaction was tested with the GLIM package on a SIEMENS 7880 mainframe. A work region of 7,000 KByte and about 60 min CPU time was necessary.] Louviere and Woodworth *(17)* suggest as an alternative to adjust the degrees of freedom of the standard t-test of the regression coefficients from degrees of freedom (DOF) = number of respondents times number of questions to DOF = number of respondents. This adjustment underestimates the significance of the factors but is on the safe side. Tables 3 and 4 give the results of both tests for the two data sets. The regression equations used to calculate the t-values included the interaction terms of interest.

The results for both groups show the high significance of all but one factor, length. This result is explained in part by the interaction between length and traffic volumes as will be explained shortly. As shown by the t-values, all of the factor impacts have the expected positive sign. Comparison of the two significance tests confirms the conservative nature of the DOF adjustment. The underestimation of significance leads in two cases to rejection of the null hypothesis (land use and bicycle facilities in Table 4). It is preferable to use the F-test, but for large data sets only the t-test is computationally feasible.

Plots of the marginal means of the factors (Figures 1 and 2) show that for both students and club members reductions in traffic volumes and slopes result in an approximately linear increase in the evaluation. The improvement in the other three significant factors has a nonlinear impact on increases in the evaluation. For these three factors the first improvement is much more important than the second. For example, the change from riding through an industrial area to riding through a residential area is about three (students) to eight (Bombay Bicycle Club) times greater than the change from residential to park areas. The members of the bicycle club are also in relative terms more sensitive to the change from no facility to a bike lane than are the students, whereas the students are more sensitive to the change from bike lane to bike path. For both groups surface quality is the most important variable. The largest overall increase in the evaluation is due to improvements in surface quality.

Identification of Interaction

As the data in Table 4 indicate, the two significance tests give different results for the significance of the interaction terms. None of the adjusted t-values for the interaction terms are significant at the 0.05 level; however, the F-test gives three interaction terms that are significant at the 0.05 level and one at the 0.10 level. The results from the adjusted t-value test are supported by the minimal increase in explained variance provided by the four significant F-test interaction terms. Also, none of the interaction terms for the student data set (Table 3) has significant adjusted t-values at the 0.05 level. Nevertheless, nonlinearities in the factor relationships may distort the analysis of the interaction terms. Thus it is useful to examine the significant interactions graphically using plots of the marginal means.

Figures 3–6 show the nature of the significant interactions identified by the F-test in Table 4. In general, the interactions are small and many of the underlying relationships are nonlinear. The

TABLE 3 SIGNIFICANCE TESTS FOR THE NORMALIZED RESPONSES OF STUDENTS

Factor	F-Test $MS(F)$	$MS(F*R)$	F	Adjusted t-Value	Marginal Means 0	1	2
L: Length	0.3	0.3	0	—[a]	.00	.02	−.02
V: Volume	73.0	0.7	104[b]	2.44[c]	−.28	.05	.23
S: Slope	126.2	0.7	180[b]	3.33[b]	−.36	.05	.31
LU: Land use	122.9	1.1	112[b]	2.77[c]	−.37	.12	.26
BF: Facilities	108.2	0.8	135[b]	2.62[c]	−.35	.12	.23
SQ: Surface	238.1	1.2	199[b]	4.23[b]	−.51	.11	.40
DOF	2	244		122			
Interactions		—[d]		—[e]			

[a]Not significant at $\alpha = 0.05$ for unadjusted t.
[b]Significant at $\alpha = 0.005$.
[c]Significant at $\alpha = 0.05$.
[d]Not computed for reasons stated in the text.
[e]Not significant at $\alpha = 0.05$ for adjusted t.

TABLE 4 SIGNIFICANCE TESTS FOR THE NORMALIZED RESPONSES OF THE BOMBAY BICYCLE CLUB

Factor	*F*-Test *MS(F)*	*MS(F*R)*	*F*	Adjusted *t*-Value	Marginal Means 0	1	2
L: Length	0.1	0.2	0	–[a]	–.02	.02	.03
V: Volume	78.1	0.6	130[b]	3.46[b]	–.37	.02	.34
S:Slope	17.1	0.5	38[b]	1.64[c]	–.17	.01	.16
LU:Land use	45.2	0.7	65[b]	1.54	–.31	.13	.19
BF: Facilities	47.8	1.1	42[b]	1.51	–.32	.15	.18
SQ: Surface	200.7	1.2	167[b]	4.07[b]	–.63	.15	.48
DOF	2	134		67			
*L*V*	1.3	0.5	3[d]	–[a]			
*L*S*	0.3	1.1	0	–[a]			
*L*LU*	0.1	0.3	0	–[a]			
*L*BF*	0.3	0.5	1	–[a]			
*L*SQ*	0.2	0.3	1	–[a]			
*V*S*	2.9	2.7	1	–[e]			
*V*LU*	1.5	2.4	1	–[a]			
*V*BF*	2.6	0.3	9[b]	–[e]			
*V*SQ*	0.7	1.0	1	–[a]			
*S*LU*	2.4	3.0	1	–[a]			
*S*BF*	0.5	0.2	2[c]	–[a]			
*S*SQ*	1.4	1.6	1	–[a]			
*LU*BF*	1.7	0.5	4[b]	–[a]			
*LU*SQ*	0.7	1.3	0	–[e]			
*BF*SQ*	0.3	0.2	1	–[a]			
DOF	4	268		67			

[a]Not significant at $\alpha = 0.05$ for unadjusted *t*.
[b]Significant at $\alpha = 0.005$.
[c]Significant at $\alpha = 0.1$.
[d]Significant at $\alpha = 0.05$.
[e]Not significant at $\alpha = 0.05$ for adjusted *t*.

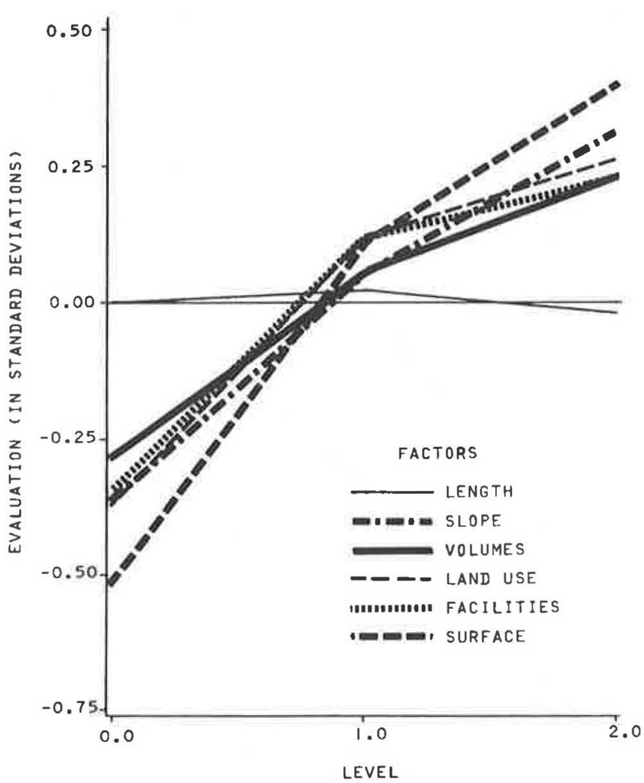

FIGURE 1 Marginal means by factor (students).

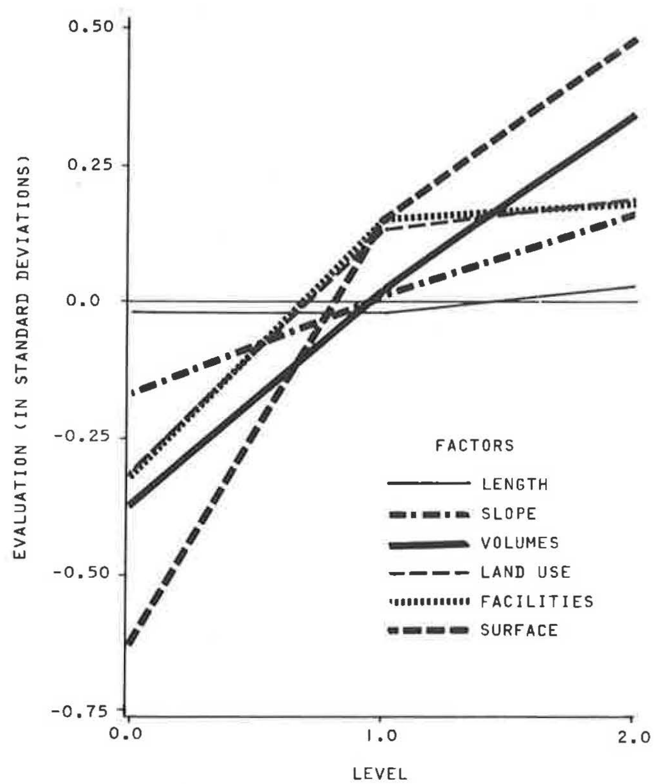

FIGURE 2 Marginal means by factor (Bombay Bicycle Club).

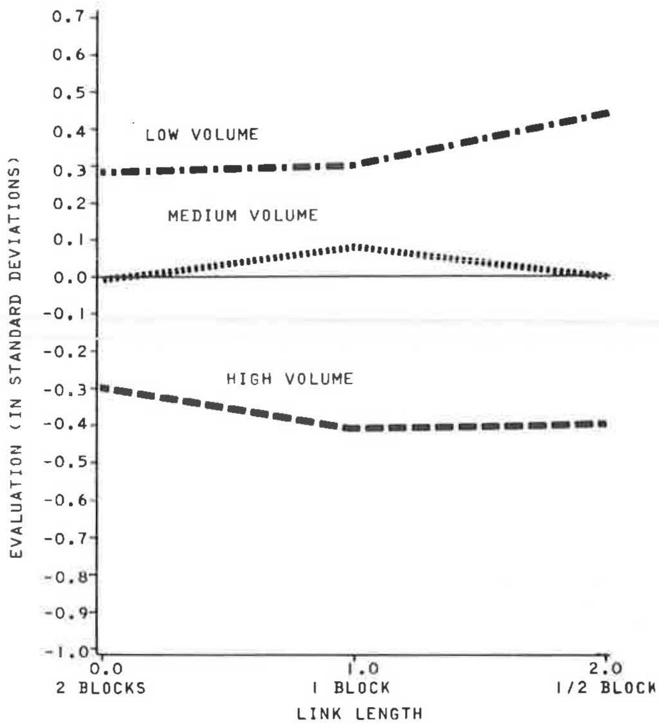

FIGURE 3 Interaction of link length and traffic volume (Bombay Bicycle Club).

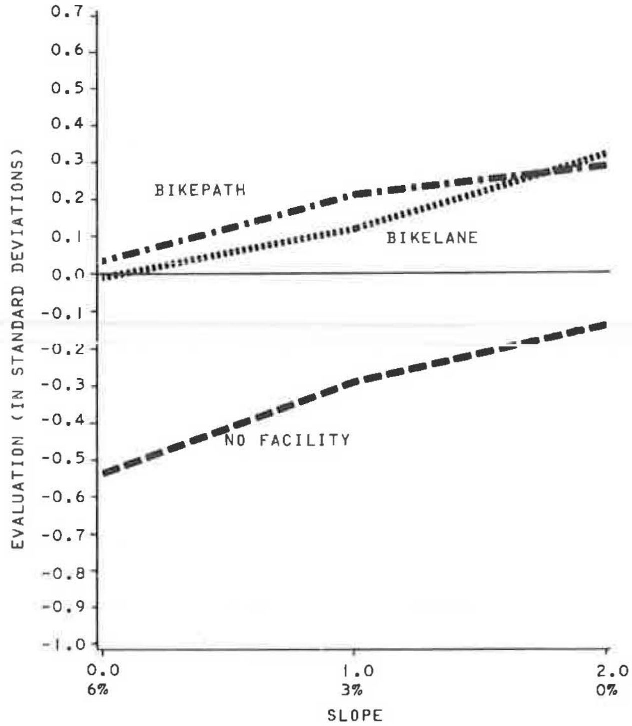

FIGURE 5 Interaction of slope and bicycle facilities (Bombay Bicycle Club).

nonlinear relationships suggest that quadratic terms may be appropriate.

An explanation for the lack of significance of length is provided by Figure 3. For low traffic volumes bicycle club members' link ratings increase as link length decreases (increases in level), and the opposite is true for high traffic volume links. The two effects cancel each other with the result that the curve for length alone is flat. The observed interaction of length and volume is logical in that the increase in the number of intersections resulting from short links would probably not cause significant delay at low volumes but would at high volumes.

The two-way interactions between bicycle facilities and the

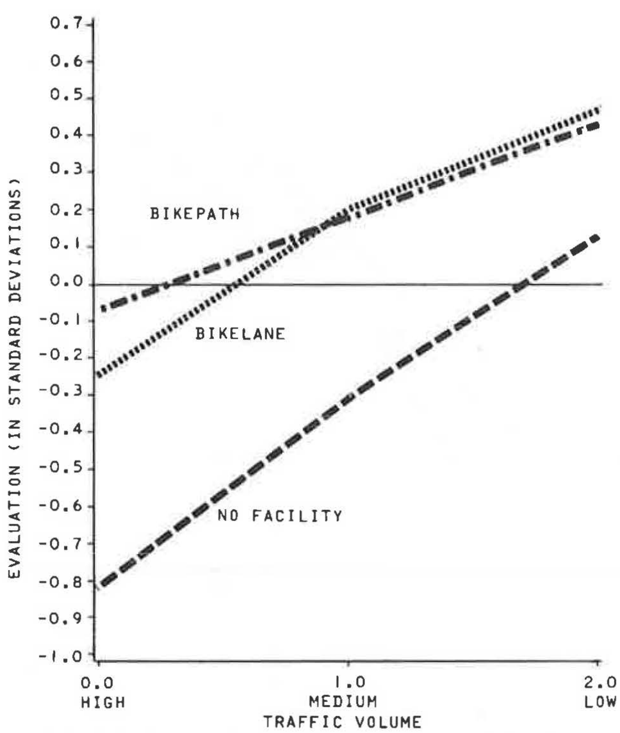

FIGURE 4 Interaction of traffic volume and bicycle facilities (Bombay Bicycle Club).

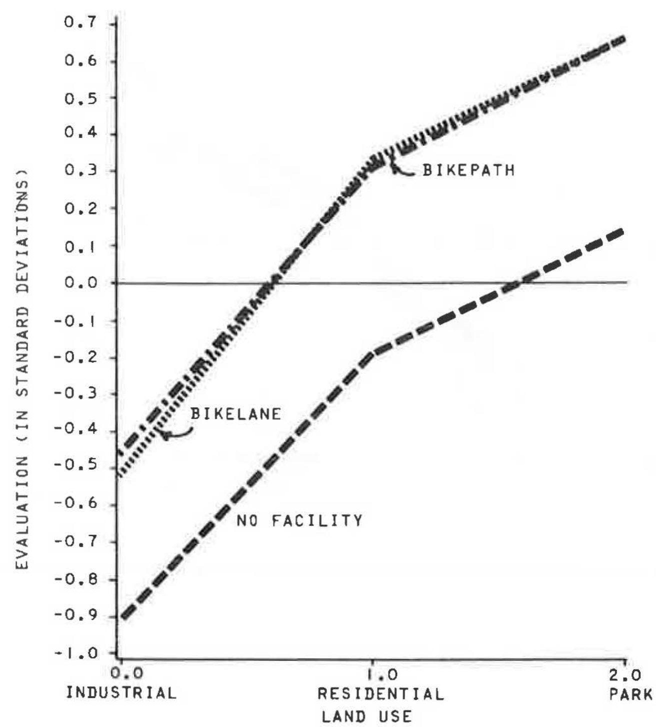

FIGURE 6 Interaction of land use and bicycle facilities (Bombay Bicycle Club).

three factors—volume, slope, and land use—are shown in Figures 4–6. In all three cases there is little difference between the curves for bike lanes and bike paths, which is consistent with the basic relationship for bicycle facilities shown in Figure 2.

The interaction between volume and bicycle facilities shown in Figure 4 is logical in that changes in traffic volumes have a greater impact on the link ratings when the bicyclists are mixed with automobile traffic (no facility) than when they are protected by a bike lane or bike path. A similar but smaller interaction between slope and bicycle facilities is shown in Figure 5. Slopes have less of an impact on the ratings when the bicyclists are using a bike lane or bike path.

Finally, the curves for the interaction between land use and bicycle facilities (Figure 6) when viewed in terms of linear approximations to the individual curves show little evidence of any significant interactions. Nevertheless, the F-test indicated significance at the 0.005 level. This inconsistency plus the low explanatory power of the interactions as a group suggest that as a first approximation the interactions can be neglected.

Linear Regression Analysis

In the second stage of the analysis the partial utility functions were estimated for both groups with piecewise-linear and linear multiple regression. The interaction terms were not included because they had been found to be generally nonsignificant. The piecewise-linear regression used two dummy variables for each factor, one for the high level and one for the low level. The coefficients therefore indicate improvement (deterioration) with respect to the middle level in multiples of the standard deviation of the responses. The results are given in Table 5.

$$R_i = \beta_0 + \beta_1{*}L + .. + \beta_6{*}SQ \quad \text{linear model}$$

$$R_i = \beta_0 + \beta_{10}{*}L_0 + \beta_{12}{*}L_2 + .. + \beta_{62}{*}SQ_2$$
piecewise-linear model

where R_i is the ith response (evaluation) to the specified link attributes L (length) through SQ (surface quality), L_0 and L_2 are the dummy variables for the zero and second levels of link length, respectively, and so forth. The constant term for the linear model reflects the worst-case situation in which the term for the linear model reflects the worst-case situation in which all of the factors are zero (lowest level) whereas in the piecewise-linear case it reflects the response in which all of the factors are at their mid-level.

As the data in Table 5 indicate, all of the linear model regression coefficients except the length coefficient are significant at the 0.05 level based on adjusted t-values and have the appropriate sign. In contrast, a number of the piecewise model coefficients are not significant, which in most cases is the result of nonlinearities in the curves. The piecewise models do have a higher explanatory power, but the increase is not large.

If the regression coefficients for the students are compared with those for the bicycle club, there appear to be some substantial differences. For example, in the linear equations the impact of the slope variable for the students is twice that for the bicycle club. Although a statistical test of the differences between the individual regression coefficients shows no significant differences, at least in general terms bicycle club members react more strongly to traffic volumes and surface quality whereas students are somewhat more sensitive to slopes, land use, and bicycle facilities. A statistical test for the overall equality of the two sets of regression coefficients was not run *(18)*.

TABLE 5 RESULTS OF REGRESSION ANALYSIS

Factor and Level[a]	Students Linear Coefficient	Students Linear Adjusted t	Students Piecewise Coefficient	Students Piecewise Adjusted t	Bombay Bicycle Club Linear Coefficient	Bombay Bicycle Club Linear Adjusted t	Bombay Bicycle Club Piecewise Coefficient	Bombay Bicycle Club Piecewise Adjusted t
L: Length	–[b]	–			–[b]	–		
Low			–[b]	–			–[b]	–
High			–[b]	–			–[b]	–
V: Volume	.26	3.22[c]			.36	3.4[c]		
Low			–.35	2.1[d]			–.40	1.9[e]
High			.17	1.0			.32	1.5[f]
S: Slope	.34	4.0[c]			.17	1.6[e]		
Low			–.41	2.5[d]			–.19	0.9
High			.27	1.6[e]			.15	0.7
LU: Land use	.32	3.8[c]			.25	2.3[d]		
Low			–.49	2.9[c]			–.47	2.6[d]
High			.14	0.9			–[b]	–
BF: Facilities	.30	3.6[c]			.26	2.4[d]		
Low			–.48	2.9[c]			–.50	2.7[d]
High			.13	0.9			–[b]	–
SQ: Surface	.45	5.4[c]			.56	5.2[c]		
Low			–.62	3.8[c]			–.78	3.7[c]
High			.29	1.8[e]			.35	1.7[e]
Constant	–1.67	8.3[c]	.45	2.0[d]	–1.60	6.3[c]	.50	2.1[d]
R-square	.40[c]		.42[c]		.43[c]		.46[c]	
Total sum of squares			3321				1691	

[a]Low level = 0 and high level = 2.
[b]Not significant at α = 0.05 for unadjusted t.
[c]Significant at α = 0.005 for adjusted t.
[d]Significant at α = 0.05 for adjusted t.
[e]Significant at α = 0.05 for adjusted t.
[f]Significant at α = .25 for adjusted t.

TABLE 6 RESULTS OF SEGMENTATION ANALYSIS

	Inexperienced Students[a]		Experienced Students[b]	
Factor	Coefficient	Adjusted t	Coefficient	Adjusted t
L: Length	–[c]	–	–[c]	–
V: Volume	.40	1.6[d]	.24	2.8[e]
S: Slope	.35	1.4[d]	.34	3.8[f]
LU: Land use	.27	1.1	.32	3.7[f]
BF: Facilities	.27	1.1	.30	3.5[f]
SQ: Surface	.27	1.1	.48	5.4[f]
Constant	−1.55	2.6[e]	−1.69	8.0[f]
R-square	.34		.41	
Total sum of squares	416		2,805	
Respondents	16		106	
F-value		22.9		

[a]Self-evaluation ≤ 3.
[b]Self-evaluation ≥ 4.
[c]Not significant at $\alpha = 0.05$ for unadjusted t.
[d]Significant at $\alpha = 0.25$ for adjusted t.
[e]Significant at $\alpha = 0.05$ for adjusted t.
[f]Significant at $\alpha = 0.005$ for adjusted t.

Segmentation Analysis

It was possible to segment the students according to their self-evaluation using an F-test for the equality of sets of coefficients in two regression equations *(18)*. Linear regression equations were used for the segmentation because their explanatory value is not much smaller than the value for the piecewise-linear regression. The students with a self-evaluation of three and below had a set of coefficients significantly different from the students with a self-evaluation of four and above at the 5 percent level. Although segmentation of the students hardly increased the explanatory power of the resulting equations, segmentation is important to see the differences between the two groups. Segmentation based on age, sex, or car ownership was not possible.

Comparison of the two subgroups in Table 6 shows that certain variables gain or lose importance with increasing experience: Traffic volumes and the change from bike lanes to bike paths lose importance. Surface quality, land use, and the change from no facility to a bike lane gain importance. Experienced bicyclists are less afraid of sharing the street with other traffic but are sensitive to environmental influences, such as the abutting land use or the surface quality of the road. In comparison with the members of the Bombay Bicycle Club, the more experienced students are not as sensitive to traffic and much more sensitive to slopes.

The segmentation analysis was also performed for the responses of the Bombay Bicycle Club. It was not possible to detect any significant differences between subgroups for any of the available variables. In contrast with the student data set, it was not possible to test for the differences between members with self-evaluation of three and below and the rest of the sample because too few members had classified themselves in the low category.

The relative importance of the variables in this study can be compared with the results of Bradley and Bovy's study *(9)* by using the results for both the experienced students and the members of the Bombay Bicycle Club. For both groups the variable "surface quality" has approximately twice the importance of the variables "traffic volumes" and "bike facilities," which is consistent with Bradley and Bovy's results.

CONCLUSIONS

The study demonstrated that it is possible to use functional measurement to estimate one of the partial utility functions of the hypothesized overall utility function of route choice. The utility of the individual links was estimated as a function of six link attributes. All but one of the attributes have significant main effects at the 5 percent level.

Three different groups of bicyclists were identified: inexperienced students; experienced students; and older, experienced bicyclists. The results showed that traffic volume, which can be viewed as a surrogate for safety, is the most important factor for inexperienced bicyclists. In contrast, the experienced bicyclists stress surface quality, which is a surrogate for the ability to travel at higher speeds.

The student responses are similar with respect to slope, land use, and bicycle facilities. Overall, students are much more sensitive to slope than are older, experienced bicyclists. Differences between the students' and the older, experienced bicyclists' responses to land use and bicycle facilities are small. The experienced students, however, are much less sensitive to traffic volume than are the older, experienced bicyclists.

Application of both F- and t-tests indicated that two-way interaction terms were generally not significant. Graphic analysis of the four significant interactions from the F-test showed that magnitudes were small and subject to logical explanations. As a first approximation, interaction effects can be ignored, which greatly reduces the size of the experimental design required for future research.

The results of this study indicate the need for bicycle planning based on the various subgroups of bicyclists. Bike lanes or paths through residential neighborhoods can help inexperienced and older, experienced bicyclists who want to avoid high traffic volumes but are less likely to be attractive to the more experienced student bicyclists who want high-quality surfaces that are relatively flat.

The next steps in the effort to develop a route choice model for bicyclists are the estimation of the partial utility function for the evaluation of intersections and the incorporation of these two parts into the overall utility function. By using the overall route choice work by Bradley and Bovy *(9)* as a basis, it may be possible to go directly to estimation of the overall utility function, again using functional measurement. Key methodological issues include the representation of intersection characteristics, specification of a partial utility function for a sequence of nonhomogeneous links in a route, and integration of partial functions for both intersections and sequences of links into an overall route utility function. Validation of this last step will require the collection of an extensive set of revealed-preference data. The repetition of this study with a representative sample of bicyclists would be necessary to identify all subgroups of bicyclists and their specific needs.

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REFERENCES

1. M. Wachs. "Relationships Between Driver Attitudes Toward Alternate Routes and Driver and Route Characteristics." In *Highway Research Record 197*, HRB, National Research Council, Washington, D.C., 1967, pp. 70–87.
2. S. M. Carpenter. *Driver's Route Choice Project—Pilot Study.* Report 085/WP42. Transport Studies Unit, Oxford University, England, 1979.
3. N. H. Anderson. "Algebraic Models in Perception." In *Handbook of Perception* (R.C. Chaterette and M.P. Friedman, eds.), Academic Press, New York, Vol. 2, 1974.
4. J. J. Louviere et al. *Laboratory Simulation versus Revealed Preference Method.* Technical Report 127. Institute of Urban and Regional Research, University of Iowa, Iowa City, 1981.
5. G. Kocur et al. *Guide to Forecasting Travel Demand with Direct Utility Assessment.* UMTA, U.S. Department of Transportation, 1982.
6. W. Upcott. *Cyclist's Route Choice.* M.S. thesis. Cranfield Institute of Technology, Cranfield, Bedfordshire, England, 1976.
7. B. Teichgraeber. *Wegewahl von Radfahrern.* M.S. thesis. Institut für Städtebau und Landesplanung, Universität Karlsruhe, Federal Republic of Germany, 1982.
8. J. Krause. *Radfahren in der Stadt.* Institut für Städtebau, Wohnungswesen und Landesplanung, Technische Universität Braunschweig, Federal Republic of Germany, 1984.
9. M. A. Bradley and P. H. L. Bovy. "A Stated Preference Analysis of Bicyclist Route Choice." Presented at Planning and Transport Research and Computation Summer Annual Meeting, Brighton, England, 1984.
10. B. Kroll and M. Ramey. Effect of Bike Lanes on Driver and Bicyclist Behavior. *Journal of the Transportation Engineering Division*, ASCE, Vol. 103, No. TE2, March 1977, pp. 243–256.
11. T. Walsh. *Development of a Comprehensive Bikeway Program.* Report to the Madison Common Council, Madison, Wis., 1975.
12. B. Kroll and R. Sommer. Bicyclist Response to Urban Bikeways. *Journal of the American Institute of Planners*, 1976, pp. 42–51.
13. D. Y. Lott, T. Tardiff, and D. F. Lott. "Evaluation by Experienced Riders of a New Bicycle Lane in an Established Bikeway System." In *Transportation Research Record 683*, TRB, National Research Council, Washington, D.C., 1978, pp. 40–46.
14. P. Ambrosius. *Nachfrage im Fahrradverkehr—Ansätze zur Quantifizierung des Einflusses von Radverkehrsanlagen.* Ph.D. dissertation. Institute für Verkehrswesen I, Ruhr Universität Bochum, Federal Republic of Germany, 1984.
15. J. J. Louviere and R. L. Meyer. A Composite Attitude-Behavior Model of Traveler Decision Making. *Transportation Research*, Vol. 15B, 1981, pp. 411–420.
16. W. S. Conner and M. Zelen. *Fractional Factorial Experiment Designs for Factors at Three Levels.* Applied Mathematics Series 54. National Bureau of Standards, 1959.
17. J. J. Louviere and G. Woodworth. Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. *Journal of Marketing Research*, Vol. 20, Nov. 1983, pp. 350–367.
18. J. Johnston. *Econometric Models.* McGraw-Hill Book Co., New York, 1970.

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Effects of Capacity Constraints on Peak-Period Traffic Congestion

MOSHE BEN-AKIVA, ANDRE DE PALMA, AND PAVLOS KANAROGLOU

The model of Ben-Akiva, Cyna, and de Palma is extended to represent trip departure time and route choice decisions when total demand is elastic. The simple case treated has two parallel routes with travelers jointly selecting route and departure time. The delays are assumed to occur at bottlenecks of limited capacity (bridge, tunnel, etc.) and a simple queueing model is employed to determine waiting time as a function of queue length at the time of arrival at the end of the queue. The day-to-day adjustment of the distribution of traffic is derived from a dynamic Markovian model. Numerical simulation experiments are performed to demonstrate the possible changes in the pattern of peak-period congestion when capacity of a bottleneck is changed. The results demonstrate some of the interdependencies that may exist among different bottlenecks in a road network. It is shown, in particular, that, in the presence of elastic demand, congestion may persist even when capacity of a bottleneck is expanded to meet the highest level of existing traffic flows. This does not mean, however, that expanding the capacity of a bottleneck and thus diverting trips from other routes cannot be a successful strategy for reducing schedule delays and traffic congestion along other routes, if that is the objective of traffic management. In addition, it is shown that if the capacities of the bottlenecks remain constant on average, but fluctuate from day to day because of stochastic factors (such as weather conditions), average traffic delays tend to increase. The modeling approach presented in this paper can also be used for policy analyses such as finding the optimal capacity expansion, the optimal coarse toll or time-dependent toll, the impact of information in situations of stochastic capacity, and the impact of changing the characteristics of an alternative travel mode.

Traffic congestion occurs at critical bottlenecks on the network where large traffic volumes and limited roadway capacity cause queues to develop. A bottleneck may occur at a point where roadway capacity is reduced, such as a merge area, a bridge, a tollgate, or a tunnel. It is assumed that, as soon as the arrival flow at the bottleneck is larger than its capacity, a queue develops and the departure flow from the bottleneck is equal to its capacity. The limited resources available for the expansion of highway networks in dense urbanized areas are likely to cause further increases in levels of congestion. In this paper a model of peak-period traffic congestion is used to analyze the effects of capacity constraints. The model is applied to a simplified network to predict the lengths of the queues at different times. Simulation results of the model in a prototypical situation demonstrate the effects of changing capacity on the pattern of traffic congestion during a peak period.

The model assumes that a commuter may choose to avoid long queues by trading off the difference between actual and desired arrival times (termed schedule delay) against shorter travel time. For a discussion and empirical estimates of this trade-off, see, for example, Kraft and Wohl *(1)*, Cosslett *(2)*, Small *(3)*, Abkowitz *(4)*, and Hendrickson and Plank *(5)*. Equilibrium models of peak-period traffic congestion that incorporate this trade-off for a network with a single bottleneck facility were developed by Vickery *(6)*, Henderson *(7)*, Hendrickson and Kocur *(8)*, and Fargier *(9)*. A stochastic extension for this problem was developed by de Palma et al. *(10)*, and its dynamic version was analyzed by Ben-Akiva et al. *(11)*.

Although many useful results were obtained from these models, their assumption of inelastic total volume is often not satisfied. The presence of congestion after a significant increase in capacity is often attributed to diverted and induced demands. Additional travelers are attracted by the expanded facility and consequently the queues that were expected to vanish may persist *(12)*. To capture this effect the present authors use a model, recently developed by Ben-Akiva et al. *(13)*, that extends the previous work by employing an elastic demand function for the total number of road users. In the previous analyses, the total number of travelers crossing the bottleneck was fixed and only the choice of departure time was considered. However, travelers can also decide to travel or not, to choose among different destinations, to switch to alternative modes of travel, and to divert to alternative routes. A simple example would be the case of two parallel routes in which travelers are jointly selecting a route and a departure time. In this case, it is also useful to include the option of not traveling.

The numerical simulations that are presented in this paper are concerned with the case of two parallel roads, a high-capacity expressway and a shorter distance arterial. This example is used to demonstrate the effects of changes in capacity on the pattern of peak-period congestion.

The results presented in this paper could be generalized without any difficulty to more than two routes in parallel. In a companion paper, de Palma et al. *(14)* have considered the case of multiple origins, a single destination, and bottlenecks in series; this corresponds to an urban corridor situation. The simulation of general networks appears to be significantly more complex. Ben-Akiva *(15)* discusses some of the difficulties inherent in this generalization.

MODEL

Consider a network that consists of I parallel routes linking a single origin-destination pair. Let N be the number of potential travelers, each one of whom is faced with deciding whether to travel via one of the I routes. Given a decision to travel, the traveler selects a route ($i = 1, ..., I$) and a departure time (t) from the origin, $t \in [T_0, T_0 + T]$, where T_0 and $T_0 + T$ are the earliest and the latest possible departures from the origin, respectively.

It is assumed that individuals may alter their choices from day to day. The probability, $P^i(t,\omega)h$, that a given individual decides on day ω to use one of the I routes, to select route i from the I routes, and to depart from the origin during the time interval $[t, t + h[\in [T_0, T_0 + T]$ is obtained from a nested logit model. [See Ben-Akiva and Lerman *(16)* and Ben-Akiva et al. *(13)* for detailed presentations of the nested logit model and its application, respectively.] It

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views a trip as the outcome of a three-stage decision process: choice of using one of the I routes, choice of leaving during the time interval $[t, t + h[$ conditional on the choice of making a trip, and choice of using route i conditional on the previous two choices. Following Ben-Akiva et al. *(13)*, the following product of conditional probabilities is obtained:

$$P^i(t,\omega)h = \text{(Probability of a trip on day } \omega) \\ \text{(Probability of a departure between } t \text{ and } t + h \text{ given a trip on day } \omega) \\ \text{(Probability of selecting route } i \text{ given a trip departure during the period } [t, t + h[\text{ on day } \omega) \quad \text{(1a)}$$

Each probability is assumed to have the multinomial logit form with its own scale parameter; μ_1, μ_2, and μ_3 are the parameters of the route, departure time, and the travel or no travel choice probabilities, respectively. A scale parameter of a discrete choice model measures the degree of heterogeneity of preferences among individual decision makers in a market segment. The nested logit formulation for this choice probability can be expressed by

$$P^i(t,\omega)h = (\exp[V^i(t,\omega)/\mu_1]/\exp[V^*(t,\omega)/\mu_1]) \\ (\exp[V^*(t,\omega)/\mu_2]/\exp[V^*(*,\omega)/\mu_2]) \\ (\exp[V^*(*,\omega)/\mu_3]/\{\exp[V^*(*,\omega)/\mu_3] \\ + \exp[V_0/\mu_3]\}) \cdot h \quad \text{(1b)}$$

where the following composite variables are used

$$V^*(t,\omega) = \mu_1 ln \sum_{j=1}^{I} \exp[V^j(t,\omega)/\mu_1] \quad \text{(1c)}$$

$$V^*(*,\omega) = \mu_2 ln \sum_{u=T_0}^{T_0+T} \exp[V^*(u,\omega)/\mu_2] \quad \text{(1d)}$$

and where an asterisk is used to indicate that a summation has been performed over the corresponding variable, $V^i(t,\omega)$ is the systematic utility of the choice described previously, and V_0 is the utility of not using one of the I routes (i.e., the null alternative). The composite variable defined in Equation 1c is the expected maximum utility from the choice among alternative routes. The variable defined in Equation 1d is the expected maximum utility from the choice among alternative trips (i.e., combinations of departure time period and route).

The utility function of a trip via route i departing from the origin at time t during day ω is assumed for simplicity to have the following linear form:

$$V^i(t,\omega) = d^i - \alpha tt^i(t,\omega) - SD^i(t,\omega) \quad \text{(2)}$$

where

d^i = a constant specific to route i,
$tt^i(t,\omega)$ = travel time from the origin to the destination on day ω for a departure at time t via route i,
$SD^i(t,\omega)$ = the disutility of schedule delay of a trip via route i departing at time t during day ω, and
α = a constant parameter that measures the marginal disutility of travel time.

The specification of schedule delay disutility assumes that the desired period of arrival at the destination is $[t^* - \Delta, t^* + \Delta]$ where t^* denotes the center of the desired arrival period and $\Delta \geq 0$ is a measure of arrival time flexibility. (Alternatively, Δ can be interpreted as a measure of desired arrival time variability among individuals.) The arrival time at the destination for a departure at time t for a trip via route i during day ω is given by

$$t_a^i(t,\omega) = t + tt^i(t,\omega) \quad \text{(3)}$$

Denote the departure times from the origin via route i during day ω for arrivals at the destination at times $t^* - \Delta$ and $t^* + \Delta$, respectively, by $\tilde{t}^i(\omega)$ and $\tilde{\tilde{t}}^i(\omega)$ to obtain

$$\tilde{t}^i(\omega) = t^* - \Delta - tt^i(\tilde{t}^i(\omega),\omega) \quad \text{(4a)}$$

$$\tilde{\tilde{t}}^i(\omega) = t^* + \Delta - tt^i(\tilde{\tilde{t}}^i(\omega),\omega) \quad \text{(4b)}$$

In other words, departures from the origin via route i on day ω during the period $[T_0, \tilde{t}^i(\omega)]$ result in early arrivals, and those during the period $[\tilde{\tilde{t}}^i(\omega), T_0 + T]$ result in late arrivals. The disutility of schedule delay is assumed to be piecewise linear and is specified as follows:

$$SD^i(t,\omega) = \begin{cases} \beta\, [t^* - \Delta - t - tt^i(t,\omega) & \text{for } t \in [T_0, \tilde{t}^i(\omega)] \\ 0 & \text{for } t \in [\tilde{t}^i(\omega), \tilde{\tilde{t}}^i(\omega)] \\ \beta\gamma\, [t + tt^i(t,\omega) - t^* - \Delta] & \text{for } t \in [\tilde{\tilde{t}}^i(\omega), T_0 + T] \end{cases} \quad \text{(5)}$$

where β and $\beta\gamma$ are constant marginal disutility parameters. β is therefore the disutility of 1-min early arrival and $\beta\gamma$ is the disutility of 1-min late arrival.

The delay on each route is assumed to occur at a single bottleneck facility, such as a bridge or a tollgate, with a fixed capacity of s^i. The road segments before and after the bottlenecks have fixed travel times. Queues may develop only at the entrances to the bottleneck facilities. The waiting time at the entrance to a bottleneck is determined by a deterministic queueing model: it is equal to the number of vehicles in the queue at the time of arrival at the bottleneck divided by the capacity. For more details, see Equations 2–4 in Ben-Akiva et al. *(11)*.

To simulate this model, the time period $[T_0, T_0 + T]$ is divided into equal time intervals of length h. Define $R^i(t,\omega)$ to be the number of users choosing the departure time interval $[t, t + h]$ and route i. The parameter h could be interpreted as a measure of the ability of individuals to discriminate among alternative departure times. This view is supported by Mahmassani et al. *(17)* who developed an experimental procedure to study the choice of departure time and "found that the participants adjusted their departure times by multiples of 5 minutes, with a minimum adjustment interval of 5 minutes." Moreover, various values of h have been explored, and it has been found that, if h is small enough (on the order of 5 to 10 min), the results are extremely stable. In the following, $R^i(t,\omega)$ will denote the departure rate per unit of time that is equal to $R^i(t,\omega)/h$.

Following de Palma and Lefèvre *(18)* and Ben-Akiva et al. *(11)*, it is assumed that the day-to-day adjustment process used by individuals to revise their behavior can be modeled using the following set of difference equations:

$$R^i(t,\omega + 1) = R^i(t,\omega) + R\, [NP^i(t,\omega)h - R^i(t,\omega)] \quad \text{(6)}$$

where R is a constant rate at which individuals switch their choices or the probability that a randomly chosen individual will review his travel decision on a given day. Note that $[NP^i(t,\omega)h - R^i(t,\omega)]$ is

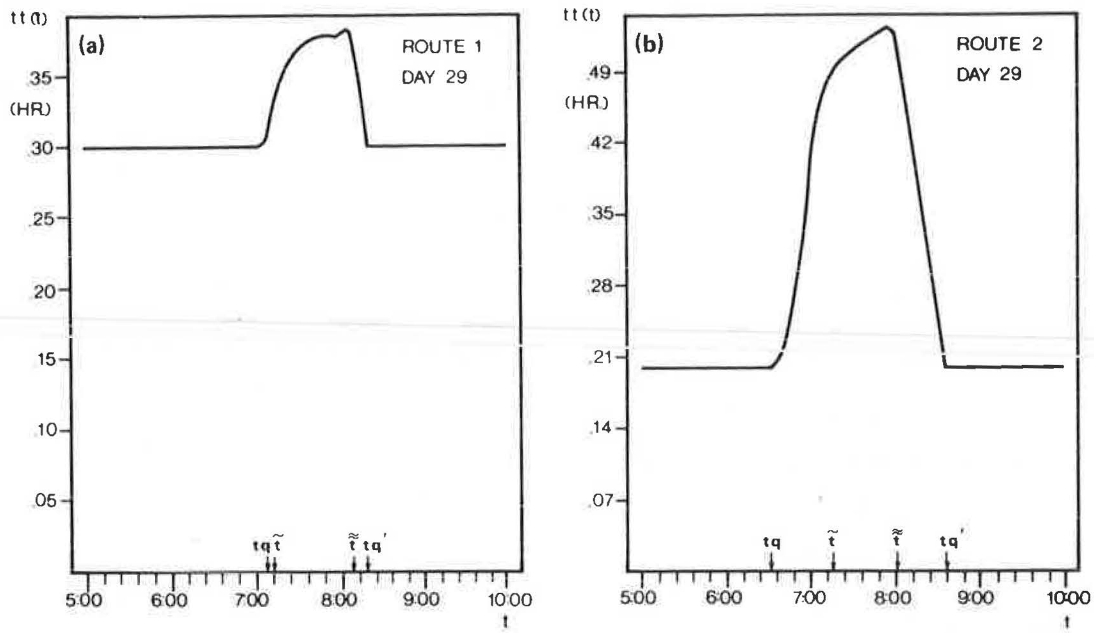

FIGURE 2 Base case stationary distributions of travel times for Route 1 and Route 2 ($s1$ = 8,000 vph and $s2$ = 3,000 vph).

runs with different parameters, it appears that these abrupt changes are caused neither by computational problems nor by the nature of the dynamic model.

In an earlier theoretical analysis of the shape of the distribution of departure and travel times, de Palma et al. *(10)* have shown that

1. The departure rate increases (decreases) exponentially for $t < t_q$ ($t > t_{q'}$);
2. When congestion is low, the distribution of departure times tends to be flat for $\tilde{t} < t < \tilde{\tilde{t}}$, for a small value of μ_2; and
3. The distribution of travel times can also be derived for the deterministic limit: it is linear for $t < \tilde{t}$ and $t > \tilde{\tilde{t}}$ and constant for $\tilde{t} < t < \tilde{\tilde{t}}$ *(25)*.

Analysis of Changes in Bottleneck Capacities

The following two changes in the capacities of the two bottlenecks are considered:

1. In the base case Route 2 is highly congested and the maximum arrival rate at this bottleneck reaches approximately 4,900 vph. As an attempt to eliminate the congestion on Route 2, its capacity is increased from 3,000 to 5,000 vph.
2. Route 1 in the base case represents a major expressway that carries almost two-thirds of the traffic in the network under study. Considered is the situation in which this highway needs to undergo major reconstruction; during the construction period the maximum peak-period capacity of this highway decreases from 8,000 to 6,000 vph (i.e., an effective loss of one lane).

The first situation is analyzed under two assumptions about the total demand: elastic total demand using the parameters of the base case and inelastic total demand with the parameters of the base case except that the total volume is constrained to be 21,698 vehicles, as in the stationary state of the base case (Table 1).

The inelastic total demand assumption is an approximation that may be more acceptable for the second situation in which the change in the capacity of Route 1 is due to road repair. Because of the temporary nature of the higher level of congestion, drivers are likely to adjust routes and departure times and maintain the same overall travel pattern in terms of origins, destinations, and modes of travel. The demand will always be elastic except when specified otherwise.

The stationary distributions for these two capacity changes are summarized in Table 1. Figure 3 shows the stationary departure rate distributions in the first situation. The distributions under the elastic and inelastic total demand assumption are quite similar, and there are no qualitative differences between the stationary distributions for the two demand assumptions. Higher capacity on Route 2 or lower capacity on Route 1 results in major shifts of traffic from Route 1 to Route 2. In the case of higher capacity on Route 2, congestion does not vanish from Route 2 even with inelastic total demand. There is a significant shift from Route 1 to Route 2 that actually eliminates congestion on Route 1. This increased capacity has substantial user benefits because the delays are significantly shorter.

Note that the importance of the temporal distribution of the demand is demonstrated by the fact that the percentage change in average delay is significantly greater than the percentage change in total volume. In the case of larger capacity on Route 2, there are no important differences between the elastic and the inelastic total demand assumptions (Table 1).

The comparisons with the base case in Figures 3a and 3b demonstrate that increasing capacity eliminates congestion on Route 1, shortens the length of the congestion period (by 25 percent) on Route 2, and decreases the average and maximum delays. It also results in a significant shift toward later departure times and a large increase [decrease] in the maximum of the departure rate distribution for Route 2 [1] because of the shift from Route 1 to Route 2. Figures 3a and 3b provide a clear demonstration of how added capacity causes an increase in traffic volume, a shift from one route to another, and a shift in the temporal distributions.

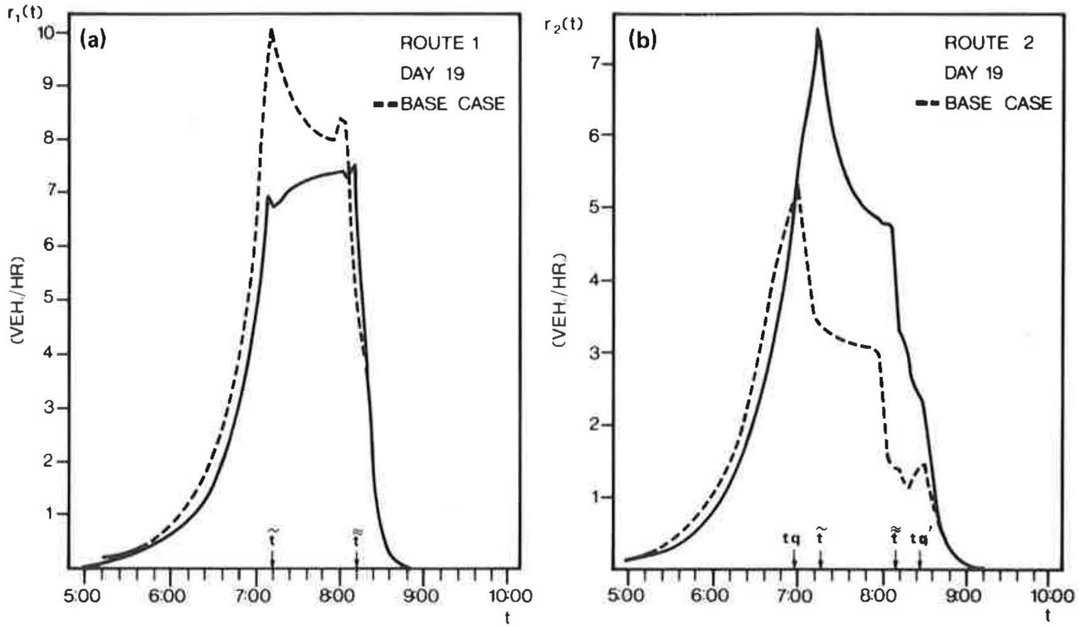

FIGURE 3 Stationary distributions of departure times for Route 1 and Route 2 (s^1 = 8,000 vph and s^2 = 5,000 vph).

The comparisons with the base case for the situation of reduced capacity on Route 1 are shown in Figure 4. In this case, the shift from Route 1 to Route 2 is less significant and the major change is a shift on both routes toward earlier departure times. There is also a smaller increase in late departures. The maximum departure rates have increased and shifted to an earlier time and the durations of the congestion periods on both routes have increased significantly. Thus the major effect of closing one lane on Route 1 is a shift of traffic from the congested on-time arrival period on Route 1 to early arrival periods on Routes 1 and 2.

In a situation of drastic change in the capacities of the bottlenecks in a highway network it is important to predict the transient adjustments of the volumes in addition to the new equilibrium state. Major reductions in capacities often occur for short periods of time when a highway section is being repaired and the dynamics of the traffic are of direct interest. For permanent changes in capacity such as the construction of an additional lane, it is also useful to study the length of the adjustment period.

The predicted dynamic evolutions of the traffic flows and delays toward their new stationary states starting from the stationary state of the base case are shown in Figure 5. The rate of convergence to a stationary state is dependent on the value of the review rate. For a high value, a convergence to a stationary state is not guaranteed. Simulation experiments consistently show that for small values of

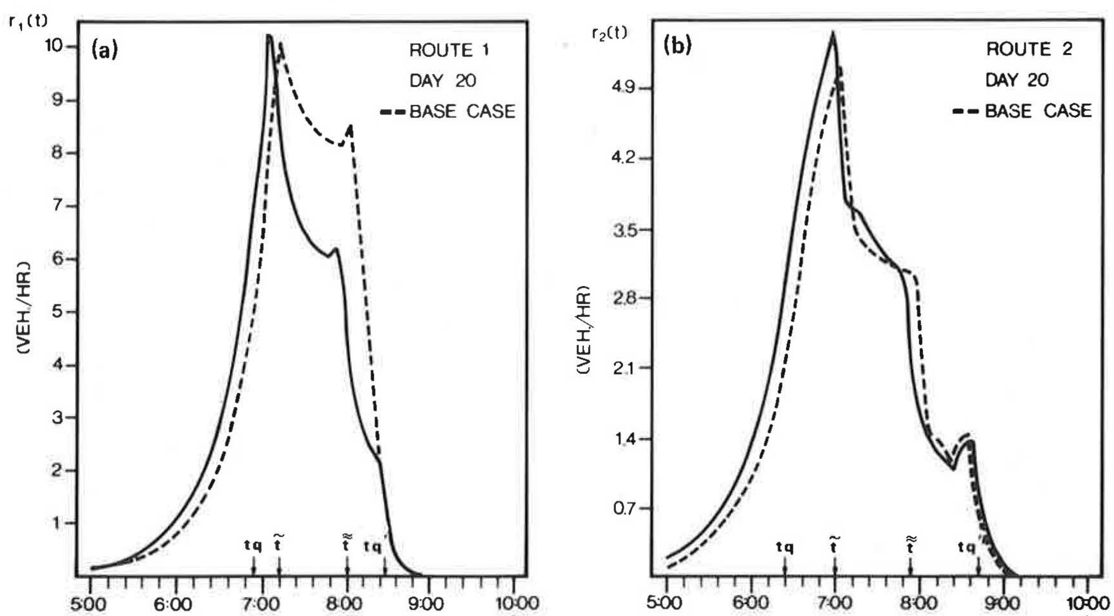

FIGURE 4 Stationary distributions of departure times for Route 1 and Route 2 (s^1 = 6,000 vph and s^2 = 3,000 vph).

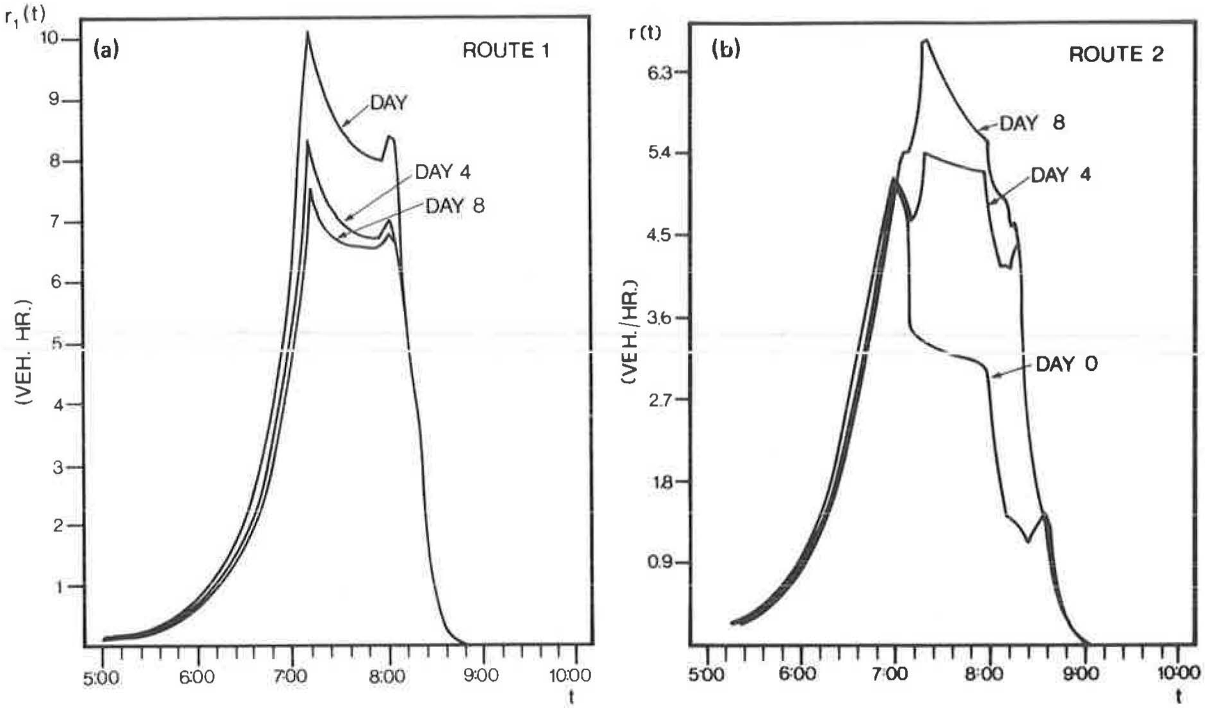

FIGURE 5 Transient distributions of departure times for Route 1 and Route 2 (s^1 = 8,000 vph and s^2 = 3,000 vph).

the review rate convergence occurs toward a unique stationary state. A value of 0.1 was selected for the simulations presented in this paper because it leads to stable stationary states after a period of 2 to 3 weeks, which is reasonable for these types of traffic adjustments. As also suggested by other simulations not presented here, the dynamic evolutions of the departure rate distributions appear to have two time scales. The first period corresponds to the major shifts among the alternative routes. During the second period significant adjustments occur in the departure time distributions while the total volume on each route remains stable. [A more detailed presentation of the dynamic evolutions in the temporal distributions of traffic flows is given elsewhere *(25)*.]

The on-time arrival period on Route 1 is shortened by only 6 min, from 58 to 52 min, and begins 15 min earlier. This result could be interpreted by noting that the length of the on-time arrival period for a deterministic choice model is equal to 2Δ, which is equal to 1 hr in the simulations *(27)*.

Adding or Closing a Route

Next is considered a change in the number of routes available between the origin and the destination (Figure 6 and Table 2). Considered first is the case in which there is only one route. In this case, the congestion level, measured by average delay, is twice its value in the base case. However, the length of the congestion period increases by only 50 percent. Because of the higher level of congestion, the volume of vehicles and the consumer surplus decrease substantially.

Second, a situation is considered in which the base case network is augmented by a third route that has a capacity of 3,000 vph and the same length as Route 1. The number of road users increases slightly (by 3 percent). The main effect is a shift from Route 1 to Route 3 (31 percent) and to a lesser extent from Route 2 to Route 3 (12 percent). Thus Route 1 is no longer congested. The level of congestion decreases on Route 2 and increases on Route 3. The average delay is approximately two times greater on Route 2 than on Route 3 because Route 2 is shorter than Route 3. The average total travel time is 0.300 hr on Route 1, 0.308 hr on Route 2, but 0.356 hr on Route 3, which implies that even on average the travel times on alternative routes are not equal. The distribution of departure time at the stationary state for Route 3 is shown in Figure 7. The distribution for Route 1 is typical of a noncongested situation *(10)*. The shape of the distributions for Routes 2 and 3 is typical of a congested situation: compare Figure 7 with the base case for Route 2 (Figure 1).

Stochastic Capacity

All previous analyses have assumed that the capacities of the bottlenecks are fixed and do not vary from day to day. However, observation of traffic flow conditions on major highways that are saturated during peak periods shows that there exist day-to-day variations in capacity in the range of ±10 percent *(28)*. These deviations may be attributed to weather conditions, the mix of vehicles in the traffic stream, accidents, roadside interruptions, and other uncontrollable stochastic events that affect the maximal flow on a congested highway. The larger maximal flows that are observed could be attributed to a homogeneous traffic stream and ideal weather conditions.

Simulation results of an extension of the model in which the capacity of a bottleneck on any given day is a random variable (which is not known to the drivers when they plan their trips) follow. Let $\bar{s}^i(\omega)$ be the capacity of route i on day ω and express it as

$$\bar{s}^i(\omega) = s^i(1 + \varepsilon_\omega), \qquad i = 1,2,\ldots,I \qquad (7)$$

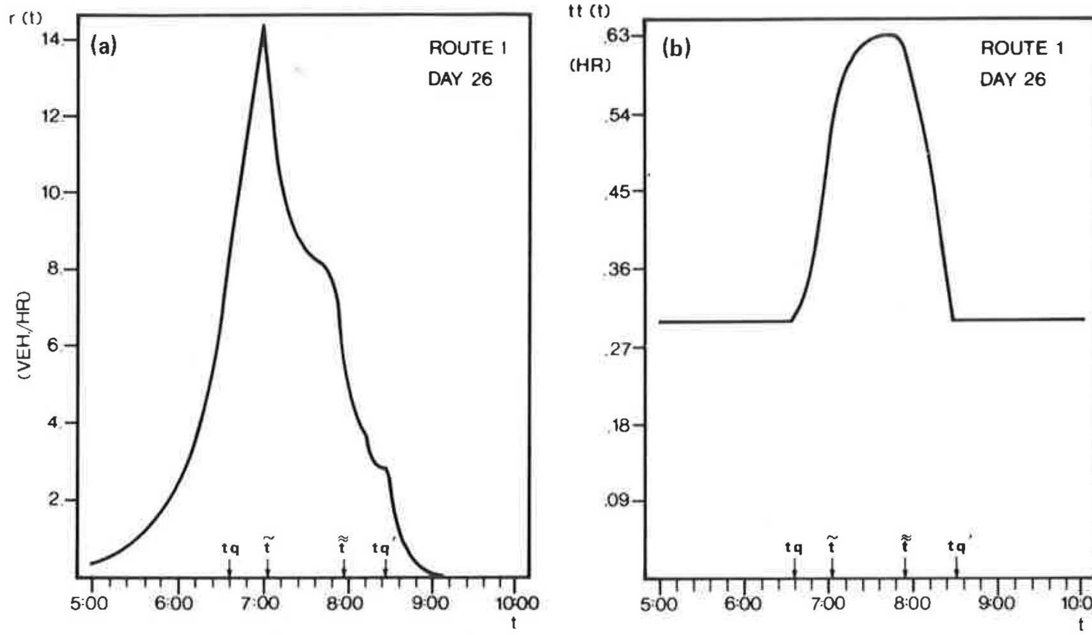

FIGURE 6 Stationary distributions of departure times and travel times for a single route (s^1 = 8,000 vph).

TABLE 2 SUMMARY OF THE STATIONARY DISTRIBUTIONS FOR CLOSING OR ADDING A ROUTE

	One Route s^1 = 8,000 vph	Three Routes s^1 = 8,000 vph, s^2 = 3,000 vph; s^3 = 3,000 vph
Total volume (vehicles)	19,654	22,343
Average delay (hr)	0.169	0.048
Average consumer surplus (utility)	4.713	6.726
Volume on Route 1 (vehicles)	19,654	9,560
Volume on Route 2 (vehicles)		6,878
Volume on Route 3 (vehicles)		5,905
Average delay on Route 1 (hr)	0.169	0.000
Average delay on Route 2 (hr)		0.108
Average delay on Route 3 (hr)		0.056
Maximum delay on Route 1 (hr)	0.331	0.000
Maximum delay on Route 2 (hr)		0.201
Maximum delay on Route 3 (hr)		0.107

where ε_ω is a uniformly distributed random variable in a range $[-m, +m]$. It is assumed that the values of ε_ω are the same for all routes and are independent from one day to another. Equation 7 implies therefore that the average capacity remains equal to s^i.

The obvious question to be addressed is: Starting from the base case and allowing the capacity to fluctuate according to Equation 7, how do traffic conditions fluctuate from day to day and what is the effect on the average flows and delays? A reduced capacity on a given day may cause travelers to shift to later or earlier departure times on the following day and possibly to less congested routes thus reducing the overall level of congestion.

On the other hand, it is expected that travel times will increase because of the convexity of the travel time function *(11)*. Finally, although on average the capacity is equal in the deterministic and the stochastic simulations, the average traffic conditions (even over a large number of days) will not be identical. The results are shown in Figure 8.

Figure 8 shows that average delay is quite sensitive to variation of m from 0 to 5 percent. Beyond this range of variations, the system appears to absorb better the stochastic variations in capacity. It is worth noting that the sensitivity of average and maximum delay to m is not the same. Maximum delay is approximately constant for $m < 0.05$ whereas average delay varies significantly in this range. An implication of these results is that, in order to have the same consumer surplus level, the capacity that is used in a deterministic model should be smaller than the average capacity. A mean preserving capacity distribution lowers the efficiency of the system as its range of fluctuations increases.

The vertical lines in Figure 8 indicate the range of day-to-day fluctuations in travel time. The ability of a network to absorb unpredictable fluctuations should be taken into consideration as well as its performance under optimal conditions. It may be preferable to have a road with stable day-to-day performance instead of a road that has larger maximum capacity but that is less reliable. A similar conclusion was reached by Kahn et al. *(29)* for a mode choice model.

The way individuals build their expectations is critical in a stochastic capacity model. Here it is assumed that the expected travel time for day ω is equal to the travel time experienced on day $\omega - 1$. In future research, more complex hypotheses should be tested. Little experimental evidence is available on this aspect of driver behavior. Moreover, little is known in general about such adjustment processes. There exist, however, some situations in which the road user may have better expectations. For example, if capacity level is a function of weather conditions, the value of capacity on day $\omega - 1$ and on day ω will be correlated. This, however, does not necessarily mean that road users will be better off. Arnott et al. *(30)* have studied a simplified version of the model presented here and have shown that this could be the case. More information provided to the road users, which makes the system more predictable, may thus lower the utility level for the

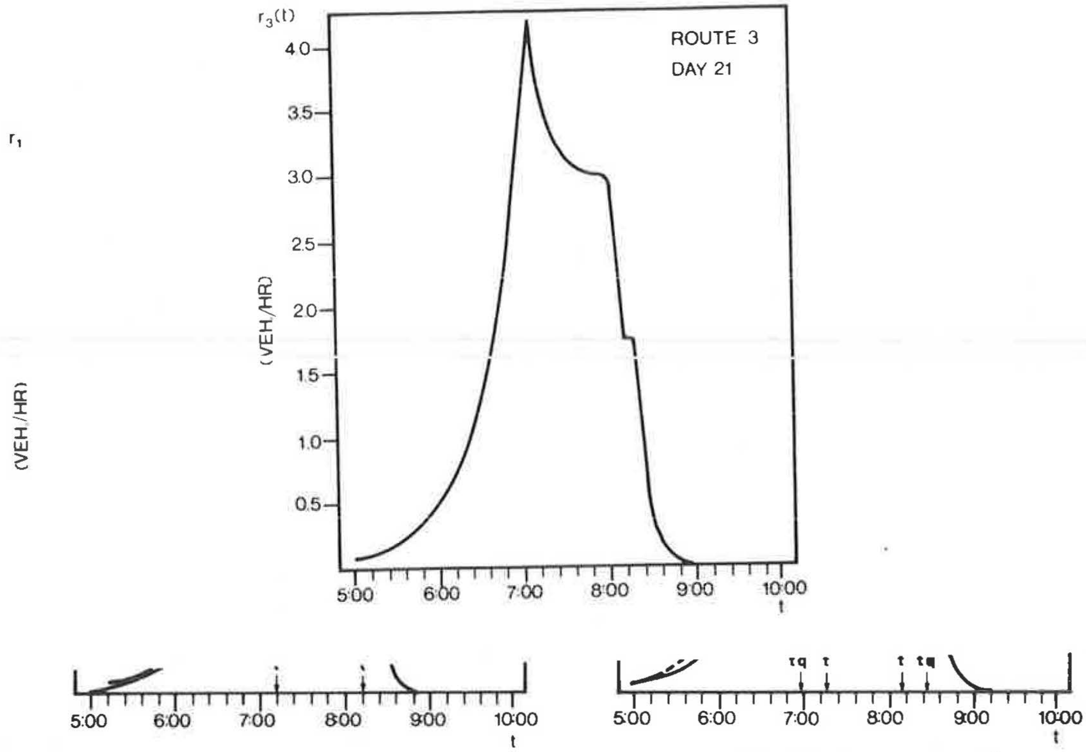

FIGURE 7 Stationary distribution of departure times in a network with three routes (s^1 = 8,000 vph, s^2 = 3,000 vph, and s^3 = 3,000 vph).

road users. This issue (which has a strong practical interest) is an important topic for future research.

CONCLUSION

The major limitations of this approach follow.

- The simplified time adjustment process, which excludes learning behavior. The mechanisms by which individuals process the information attained in their past experience should be investigated further on both theoretical and experimental grounds. This may lead to more realistic dynamic adjustment processes than those that have been considered so far. This extension will also explore the impact of detours and road construction.
- The linear specification of the utility function. It was chosen only because there does not appear to be general agreement on how to generalize the linear specification. The specification of the utility function could be changed quite easily in the simulation program that was developed.
- The simplified network that has been considered so far [see the discussion in Ben-Akiva *(15)*].
- The study of a homogeneous population without explicit treatment of taste variations. Moore et al. *(31)* found, for example, that "older workers and those living at great distances from the workplace tend to arrive earlier." This corresponds to smaller values of β but the same value of $\beta\gamma$ (Equation 5). They also found that households constrained by the presence of a working spouse and young children have less flexibility to alter arrival times with flextime. This corresponds to a smaller value of Δ (Equation 5).

The results obtained nevertheless demonstrate that the model is able to explain, at least qualitatively, the experimental properties of departure time choice situations. It is believed that the results will not be significantly different under slightly different hypotheses.

The simulation experiments have replicated important phenomena in the response of traffic flows to changes in roadway capacities. It was shown how changing the capacity of one bottleneck affects traffic conditions in a parallel facility. It was also shown that the capacity of a bottleneck may be expanded to meet the highest existing traffic flow without eliminating congestion. It is thought that the model, even with its limitations, should be able to effectively analyze simple networks.

For example, the simulation model employed in this analysis can also be used to analyze a variety of other policy measures aimed at reducing peak-period congestion. In particular, it is useful for comparisons of the effectiveness of low-capital policy options such as variable work hours and peak-load pricing with capital-intensive capacity expansions. Additional simulation results reported in Ben-Akiva et al. *(13)* replicated the phenomenon of shifting peaks that occurs when peak-period tolls are established.

Finally, further work on this modeling approach should include a detailed validation test with data from before and after an actual change in a transportation network. Attention should also be given to the theoretical properties of the stationary state of the model and the stability of its dynamic evolution. Further extensions could be directed to capturing differences among market segments with different travel behavior preferences and origin-destination patterns.

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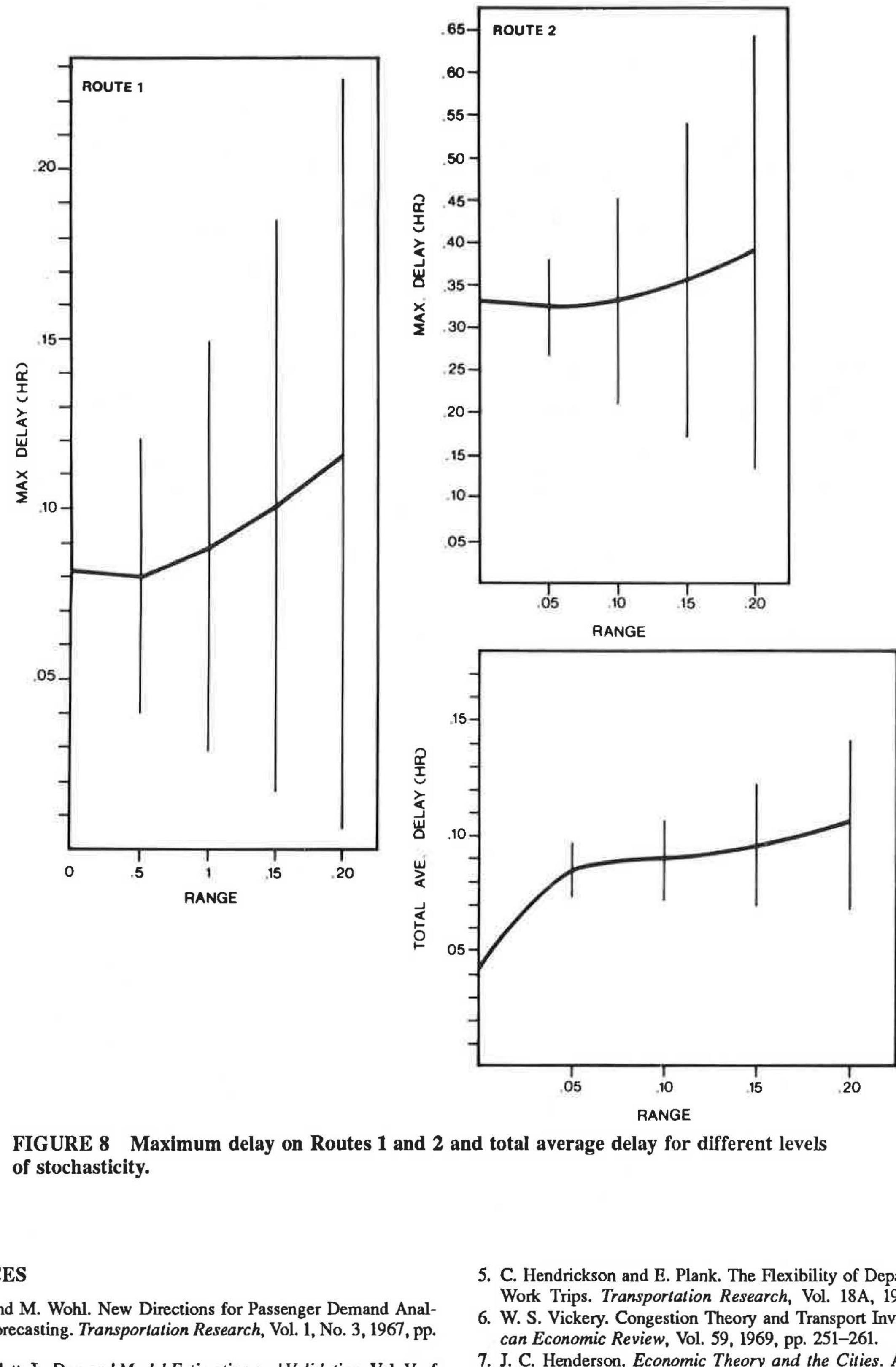

FIGURE 8 Maximum delay on Routes 1 and 2 and total average delay for different levels of stochasticity.

REFERENCES

1. G. Kraft and M. Wohl. New Directions for Passenger Demand Analysis and Forecasting. *Transportation Research*, Vol. 1, No. 3, 1967, pp. 205–230.
2. S. R. Cosslett. In *Demand Model Estimation and Validation*. Vol. V of *Urban Travel Demand Forecasting Project* (D. McFadden et al., eds.), Institute of Transportation Studies, University of California, Berkeley, 1977.
3. K. Small. The Scheduling of Consumer Activities: Work Trips. *American Economic Review*, Vol. 72, No. 3, 1982, pp. 467–497.
4. M. Abkowitz. *The Impact of Service Reliability on Work Travel Behavior*. Ph.D. dissertation. Massachusetts Institute of Technology, Cambridge, 1980.
5. C. Hendrickson and E. Plank. The Flexibility of Departure Times for Work Trips. *Transportation Research*, Vol. 18A, 1984, pp. 25–36.
6. W. S. Vickery. Congestion Theory and Transport Investment. *American Economic Review*, Vol. 59, 1969, pp. 251–261.
7. J. C. Henderson. *Economic Theory and the Cities*. Academic Press, New York, 1977, Chapter 8.
8. C. Hendrickson and G. Kocur. Schedule Delay and Departure Time Decisions in a Deterministic Model. *Transportation Science*, Vol. 15, No. 1, 1981, pp. 62–77.
9. P. H. Fargier. *Influence des mecanismes de choix de l'heure de depart sur la congestion du traffic routier*. Institute de Recherche des Transports, Arcueil, France, 1981.
10. A. de Palma, M. Ben-Akiva, C. Lefèvre, and N. Litinas. Stochastic

Equilibrium Model of Peak Period Traffic Congestion. *Transportation Science*, Vol. 17, No. 4, 1983, pp. 430–453.
11. M. Ben-Akiva, M. Cyna, and A. de Palma. Dynamic Model of Peak Period Congestion. *Transportation Research*, Vol. 18B, No. 4–5, 1984, pp. 339–355.
12. V. F. Hurdle. Equilibrium Flows on Urban Freeways. *Transportation Science*, Vol. 15, No. 3, 1981, pp. 255–293.
13. M. Ben-Akiva, A. de Palma, and P. Kanaroglou. Dynamic Model of Peak Period Congestion with Elastic Arrival Rates. *Transportation Science*, Vol. 20, No. 2, 1986, pp. 166–181.
14. A. de Palma, J.-F. Ingenbleek, C. Lefèvre, and M. Ben-Akiva. *Dynamic Model of Traffic Congestion in a Corridor*. Université Libre de Bruxelles, Brussels, Belgium, 1984.
15. M. Ben-Akiva. Dynamic Network Equilibrium Research. *Transportation Research*, Vol. 19A, 1985, pp. 429–431.
16. M. Ben-Akiva and S. Lerman. *Discrete Choice Analysis*. MIT Press, Cambridge, 1985.
17. H. Mahmassani, G.-L. Chang, and R. Herman. *Individual Decisions and Collective Effects in a Simulated Traffic System*. University of Texas at Austin, 1984.
18. A. de Palma and C. Lefèvre. Individual Decision-Making in Dynamic Collective Systems. *Journal of Mathematical Sociology*, Vol. 9, 1983, pp. 103–124.
19. J. Horowitz. The Stability of Stochastic Equilibrium in a Two-Link Transportation Network. *Transportation Research*, Vol. 15B, No. 1, 1984, pp. 13–28.
20. M. Ben-Akiva and S. Lerman. "Disaggregate Travel and Mobility Choice Models and Measures of Accessibility." In *Behavioral Travel Modelling* (D.A. Hensher and P.R. Stopher, eds.), Croom Helm, London, England, 1979, pp. 654–669.
21. K. A. Small and H. S. Rosen. Applied Welfare Economics with Discrete Choice Models. *Econometrica*, Vol. 49, 1981, pp. 105–130.
22. D. McFadden. "Economic Models of Probabilistic Choice." In *Structural Analysis of Discrete Data with Econometric Applications* (C. F. Manski and D. McFadden, eds.), MIT Press, Cambridge, 1981.
23. M. H. Ueberschaer. Choice of Routes on Urban Networks for the Journey to Work. In *Highway Research Record 369*, HRB, National Research Council, Washington, D.C., 1971, pp. 228–238.
24. M. Wachs. "Relationship Between Drivers' Attitudes Toward Alternative Routes and Driver and Route Characteristics." In *Highway Research Record 197*, HRB, National Research Council, Washington, D.C., 1967, pp. 70–87.
25. M. Ben-Akiva, M. J. Bergman, A. J. Daly, and R. Ramaswamy. "Modelling Interurban Route Choice Behavior." *Proc., 9th International Symposium on Transportation and Traffic Theory*, VNU Science Press, Utrecht, The Netherlands, 1984.
26. R. Arnott, A. de Palma, and R. Lindsey. *Economics of a Bottleneck*. Discussion Paper 636. Queen's University, Kingston, Ontario, Canada, 1985.
27. A. de Palma and R. Arnott. Usage-Dependent Peak-Load Pricing. *Economics Letters*, Vol. 20, 1985, pp. 101–105.
28. J. Van Toorenburg. *Praktijkwaarden voor de Capaciteit*. Research Report. Dienst Verkeeskunde, Rijkswaterstaat, The Netherlands, 1986.
29. D. Kahn, A. de Palma, and J. L. Deneubourg. Noisy Demand and Mode Choice. *Transportation Research*, Vol. 19B, No. 2, 1985, pp. 143–153.
30. R. Arnott, A. de Palma, and R. Lindsey. Schedule Delay and Departure Time Decisions with Stochastic Capacity. Queen's University, Kingston, Ontario, Canada, 1985.
31. A. Moore, P. Jovanis, and F. Koppelman. Modelling the Choice of Work Schedule with Flexible Work Hours. *Transportation Science*, Vol. 18, No. 2, 1984, pp. 141–164.

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APPENDIX

Base Values for Network Characteristics

	Free-flow travel time from origin to destination for Route 1 [Route 2]	0.3 hr [0.2 hr]
$s^1[s^2]$	Capacity of Route 1 [Route 2]	8,000 vph^{-1} [3,000 vph^{-1}]

Base Values for Demand Parameters

α	Marginal disutility of travel time	6.40 hr^{-1}
β	Marginal disutility of early arrivals	3.90 hr^{-1}
β_γ	Marginal disutility of late arrivals	15.2 hr^{-1}
μ_1	Heterogeneity factor of travel decision	1.0
μ_2	Heterogeneity factor of departure time choice	2.0
μ_3	Heterogeneity factor of route choice	3.0
R	Individual review rate	0.10 day^{-1}
Δ	Work start time flexibility	0.5 hr
t^*	Center of desired period of arrival	8.00 a.m.
V_0	Utility of the null alternative	0
N	Number of potentential travelers	25,000
T_0	Time of earliest possible departure	5.00 a.m.
T	Daily study period	5 hr

Changing Effects of Automobile Ownership on Household Travel Patterns

LIDIA P. KOSTYNIUK AND RYUICHI KITAMURA

This study sets forth the hypothesis that the effects of automobile ownership on household trip generation and automobile utilization are diminishing in the United States. The reasoning behind this statement is that, as motorization progressed and automobile ownership became widespread in the United States, the strong association between a household's propensity to travel and its automobile ownership, which existed in earlier stages of motorization, diminished. Therefore trip making of households can no longer be effectively explained by their level of automobile ownership. This study extends previous work of the authors in which automobile ownership effects were found to be decreasing for nuclear-family households. The relationships between household automobile ownership and a number of travel pattern indicators are examined in this study for all households contained in the 1963 and 1974 origin-destination survey results from Rochester, New York. Statistical analyses of the trip records indicate that the ability of automobile ownership to explain variations in the travel indicators has diminished over time and automobile ownership is no longer a key descriptor of household trip making. The cross-classification scheme based on household size and automobile ownership is also shown to have lost its effectiveness in household trip generation analysis. A more extensive categorization of household composition, however, has retained its explanatory power for the total number of trips generated by a household.

The models used in forecasting future travel demand rely heavily on a set of socioeconomic variables that is associated with people's propensity to travel. Among such variables is the number of automobiles owned by or available to the household *(1–4)*. Almost every model of residential trip generation or modal split developed since the 1950s has included a variable that represents automobile availability.

A frequently used procedure for household trip generation analysis classifies households according to the number of persons and the number of automobiles available and then evaluates a mean trip rate for each of the household subgroups *(5, 6)*. Frequently, other variables such as income or housing type are used in place of household size *(2, 7)*, or in some cases more than one variable (e.g., income and a descriptor of household structure) are used in addition to automobile ownership *(8)*. Implicit in the application of these classification procedures to forecasting household trip generation is the assumption that the trip rate observed for each subgroup of a cross-sectional survey sample remains unchanged over time. Automobile ownership is thus considered to be a household attribute that has the most salient, and temporally invariant, impact on the travel behavior of a household.

Automobile ownership and use, however, were changing dramatically during the time the currently used demand forecasting procedures were being formulated. The spread of automobile ownership and utilization, or motorization, in the United States, which had been taking place since the early part of this century, increased rapidly after World War II (Figure 1). In 1950, 41

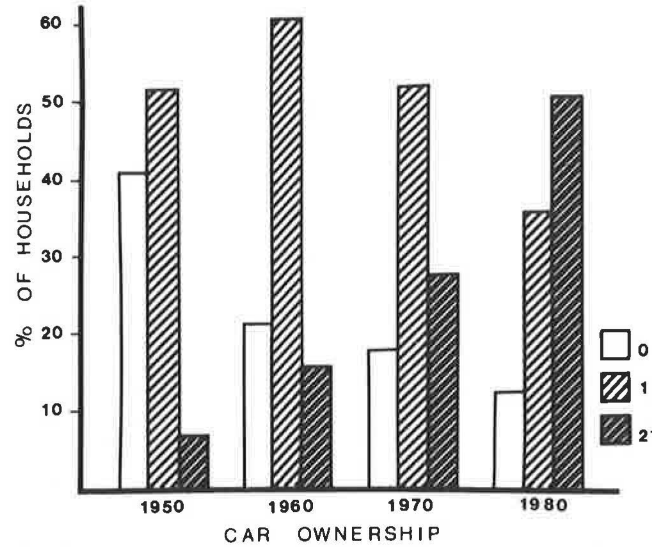

FIGURE 1 Automobile ownership in the United States: 1950–1980.

percent of households did not have automobiles available, and in 1980 this percentage was only 13 percent. The percentage of households owning two or more cars increased from 7 to 52 percent during the same time period *(9, 10)*. Currently, approximately 85 percent of the adult population of the United States is licensed to drive. However, the rate of increase in the average number of automobiles per household, shown in Figure 2, is decreasing; the average number of automobiles per household increased by only 0.1 between 1975 and 1980. It may be that motorization in the United States is entering a final phase.

The dramatic increase in automobile ownership was accompanied by substantial changes in the characteristics of automobile owners. Although only a limited number of high-income households were able to afford an automobile in the early stages of motorization, the current ranks of automobile-owning households

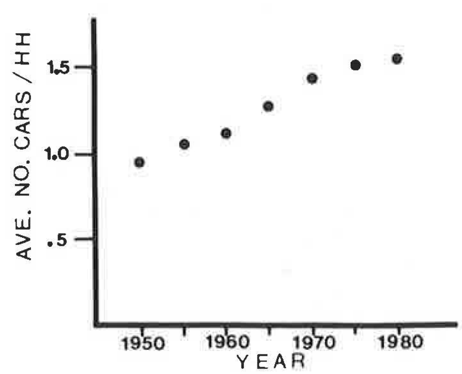

FIGURE 2 Increase in automobiles per household in the United States: 1950–1980.

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include many low-income households and households without workers. Automobile ownership by itself is no longer considered a reflection of a household's economic capability *(11)*. Because nearly 90 percent of all U.S. households own automobiles, these households are almost as heterogeneous as the entire household population and cannot be classified as a special subgroup.

In light of this expansion of automobile ownership and the changes in the characteristics of automobile-owning households, it is questionable if automobile ownership still has the same discriminating effect on travel behavior as it did earlier. Although automobile ownership has almost always automatically been chosen as a predictor of travel behavior, this practice may have been effective only in the earlier stages of motorization. At any particular time automobile ownership could be associated with trip making, but this effect may have been changing along with the changes in motorization.

In an earlier effort (*12*, p. 250), these questions were investigated using 1963 and 1974 origin-destination survey results from Rochester, New York. Analysis indicated that, between 1963 and 1974,

> more smaller, younger, and less affluent households joined the multi-car household category. No-car households in 1974 became more homogeneous in their characteristics; they were typically single-person households with no licensed drivers, no workers, low income, and consisted of older individuals. Typical one-car households also became smaller, older, and had one or no worker in 1974.

Further analysis in the same study focused on nuclear-family households (i.e., households consisting of an adult male-female couple and any children living with them). The effects of automobile ownership and several other household descriptors on a set of travel pattern indicators were explored. The set of indicators consisted of the total number of trips made by a household; the numbers of automobile trips, driver trips, and passenger trips; the numbers of trips made for purposes of work, to serve passengers, for social-recreation, and for maintenance activities; the number of trips made jointly by several household members for nonwork activities; the number of trip chains; and the mean automobile occupancy. The total time spent by the household for travel as well as the total driver time and total passenger time were also included in the set of travel pattern indicators. Statistical examination of these household travel pattern indicators offered strong empirical evidence that automobile-ownership effects had changed between 1963 and 1974. Although automobile ownership remained a "significant" predictor in 1974, its power to explain behavioral variations had substantially decreased. The same study found that the stage in the household's life cycle, a variable that clearly describes household composition in the case of nuclear households, was strongly associated with many of the indicators in 1963 and retained that strong association in 1974.

This study is an extension of the earlier study. It is an attempt to establish whether the finding of diminishing automobile-ownership effects, found for nuclear-family households, can be generalized to the entire household population and to other subgroups of households. The number of persons in a household, a simple classifier of household composition, is frequently used together with automobile ownership for trip generation analysis. Accordingly, another focus of this study is on the stability and usefulness of the household size–automobile ownership classification scheme for trip generation analysis.

SAMPLE

The statistical analysis of this study uses 1963 and 1974 origin-destination survey data from Rochester, New York, the same data sets used in a previous study *(12)*. Detailed description of the data sets can be found elsewhere *(13, 14)*, and the screening criteria used to eliminate incomplete or inconsistent household records are also discussed elsewhere *(15–17)*. The profiles of automobile-ownership subgroups obtained from the data sets are given in Kitamura and Kostyniuk *(12)*.

Table 1 gives the 1963 and 1974 households used in this study classified by the number of adults in the household, the age of children if present, age of head-of-household if no children are present, and automobile ownership. Table 2 gives the distribution of the various household types found in the data sets. It can be seen that the fraction of single-person households remained stable at approximately 14 percent between the two dates. The percentage of single-parent households, which are defined here as households with one adult and one or more children less than 15 years old, also remained stable at around 3 percent of the sample. Households with two adults with and without children make up two-thirds of

TABLE 1 1963 AND 1974 SAMPLE HOUSEHOLDS BY NUMBER OF ADULTS, LIFE CYCLE, AND AUTOMOBILE OWNERSHIP

Year	No. of Adults	No. of Automobiles	Life-Cycle Stage[a] 1	2	3	4	5	Total
1963	1	0	69	53	40	16	487	665
		≥1	119	38	47	31	295	530
	2	0	61	98	51	21	295	526
		≥1	352	1,282	1,071	291	1,179	4,175
	≥3	0	14	20	20	8	47	109
		≥1	71	148	263	184	419	1,085
Total			686	1,639	1,492	551	2,722	7,090
1974	1	1	34	12	20	8	194	268
		≥2	8	1	3	4	3	19
	2	1	62	89	71	18	236	476
		≥2	79	139	199	46	138	601
	≥3	1	2	3	13	5	26	49
		≥2	15	16	55	37	71	194
Total			200	260	361	118	668	1,607

[a]Life-cycle stages are defined in terms of the age of the household head if there is no child and in terms of the age of the youngest child, if there is one, as Stage 1: no child, age of head < 45 years, Stage 2: age of the youngest child < 5 years, Stage 3: age of the youngest child between 5 and 14 years, Stage 4: age of the youngest child ≥ 15 years, and Stage 5: no child, age of head ≥ 45 years.

TABLE 2 PERCENTAGE DISTRIBUTION OF THE 1963 AND 1974 SAMPLES BY HOUSEHOLD COMPOSITION

Household Type	1963	1974
One-adult households		
Single-person households	13.7	14.8
Single-parent households	3.2	3.0
Two-adult households		
Nuclear-family households		
With working adults[a]	53.6	53.7
Without working adults	9.3	9.1
Two adults of the same sex	3.3	4.3
Households with three or more adults		
Households with no child	7.8	7.1
Households with children	9.1	8.0
Total	100.0	100.0

[a]The households examined in Kitamura and Kostyniuk *(12)*.

TABLE 3 1963 AND 1974 SAMPLE HOUSEHOLD TRIP RATES BY AUTOMOBILE OWNERSHIP, HOUSEHOLD SIZE, AND NUMBER OF WORKERS

	Trip Rate			Sample Size		Percentage to Year Total	
	1963	1974	t	1963	1974	1963	1974
All households	7.91	8.01	0.49	7,193	1,666	100.0	100.0
Zero-automobile households	2.00	1.05	-4.38	1,314	110	18.3	6.6
One-automobile households	7.98	6.06	-8.54	4,296	713	59.7	42.8
Multiple-automobile households	12.65	10.57	-6.32	1,583	843	22.0	50.6
One-person households	1.98	2.26	1.66	960	242	13.3	14.5
Two-person households	5.18	5.57	2.02	2,001	557	27.8	33.4
Three-person households	8.07	8.05	-0.06	1,235	299	17.2	17.9
Four-person households and larger	11.58	12.83	3.35	2,997	568	41.7	34.1
Zero-worker households	2.04	3.04	4.57	1,264	344	17.6	21.1
One-worker households	8.33	7.62	-2.74	3,818	622	53.2	38.1
Multiworker households	10.72	11.02	0.91	2,098	665	29.2	40.8

both samples. The previous study *(12)* examined the composition of this group and found that nuclear families with workers constituted 54 percent of the sample in both 1963 and 1974. Approximately 9 percent of the sample is nuclear families without working adults, and 3.3 percent of the 1963 sample and 4.3 percent of the 1974 sample are households consisting of two adults of the same sex. Other non-nuclear-family households with three or more adults with and without children make up the remainder of both samples. It appears that there was little change in the distribution of household types in Rochester between 1963 and 1974. This is an important point because any changes in travel patterns in the samples found between the two years cannot be attributed to changes in the distribution of household types.

Samplewide statistics show practically identical household trip rates for the two years (Table 3). However, the trip rate decreased substantially in 1974 for all automobile-ownership subgroups, which indicates that single-car and multicar households in 1974 included more households with lower propensity to travel than in 1963 and also that no-car households in 1974, which comprise only 6.6 percent of the sample households, had extremely low mobility. The trip rates tabulated by household size, on the other hand, indicate that the household trip rate increased in 1974, especially among two-person households and households with four or more people. This tabulation suggests that the number of trips per person in 1974 was at the same level as in 1963, whereas the number of trips per automobile appears to have declined sharply in 1974.

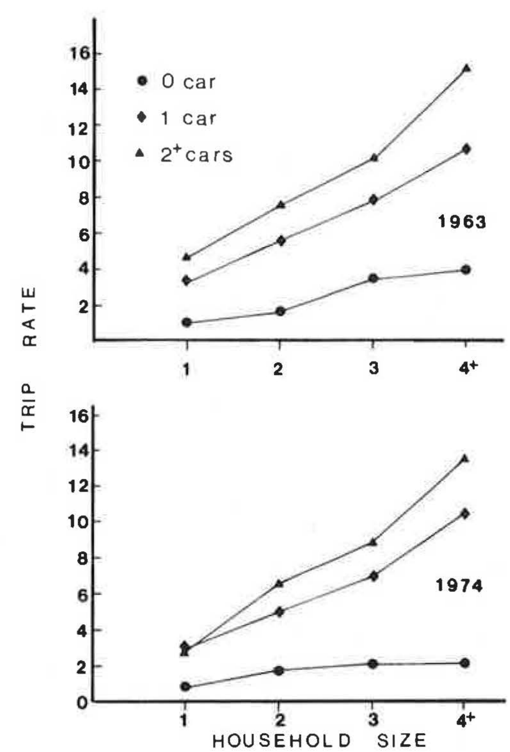

FIGURE 3 1963 and 1974 sample trip rates by household size and automobile ownership.

EFFECTIVENESS OF CROSS-CLASSIFICATION BY AUTOMOBILE OWNERSHIP AND HOUSEHOLD SIZE

The sample trip rates of household subgroups defined by the number of automobiles available and household size (Figure 3) exhibit similar patterns in 1963 and 1974. However, the trip rates of multicar households are not as distinctly high in 1974 as in 1963. In 1974 the separation between single-car households and multicar households is not as clear as in 1963.

Table 4 gives statistical support of this decreasing distinction between automobile-ownership subgroups. Analysis of variance (ANOVA) was conducted using categories of automobile ownership and household size on the following travel indicators: number of trips; number of driver trips, passenger trips, and automobile trips; travel time expenditure; and total driver time. The results indicate that the magnitude of automobile-ownership main effects decreased in 1974 for all of the travel indicators examined here. The reduction is especially noticeable for number of automobile trips and total driver trip time. For example, the automobile-ownership main effect explains 6.98 percent of the total variation in number of automobile trips in the 1963 sample. This percentage decreases to 1.11 percent in the 1974 sample. More dramatic reduction in variance explanation can be found for total driver trip time, a surrogate of household vehicle miles traveled (VMT), for which the variance explanation by the automobile-ownership main effect decreases from 10.09 to 0.98 percent. On the other hand, the difference in variance explanation between the two years is not as salient for number of trips and travel time expenditure (4.97 to 1.09 percent and 1.88 to 0.80 percent, respectively). It can be immediately inferred from the ANOVA results that household auto-

TABLE 4 ANALYSIS OF VARIANCE OF AUTOMOBILE OWNERSHIP AND HOUSEHOLD SIZE EFFECTS ON HOUSEHOLD TRIP PATTERNS

	Effect (degrees of freedom)			
	C (2)	H (3)	CH (6)	Error
No. of trips				
1963	**4.97**	**6.13**	**1.32**	87.58
1974	**1.09**	**1.16**	**0.53**	97.22
No. of driver trips				
1963	**11.86**	1.79	0.97	85.37
1974	**2.50**	0.76	0.60	96.14
No. of passenger trips				
1963	0.67	**4.14**	**0.94**	94.25
1974	0.16	0.73	0.26	98.85
No. of automobile trips				
1963	6.98	**3.91**	**1.31**	87.81
1974	**1.11**	**1.04**	**0.42**	97.44
Travel time expenditure				
1963	**1.88**	3.24	**0.52**	94.36
1974	**0.80**	0.38	0.27	98.55
Total driver trip time				
1963	**10.09**	**0.64**	0.43	88.84
1974	**0.98**	0.14	0.21	98.68

Note: Expressed as percentage of the total variation. A bold-faced value indicates that the effect is significant at $\alpha = 0.001$. C refers to automobile-ownership main effect, H to household main effect, and CH to automobile-ownership-household-size interaction effect. The 1963 sample size is 7,193 and 1974 sample size is 1,666. The categories used are 0 automobile, 1 automobile, and 2 or more automobiles and household sizes of 1 person, 2 persons, 3 persons, and 4 or more persons. It was necessary to group larger households in the 4-or-more-person category because there were no households with 5 or more people without automobiles in the 1974 sample. All rows total 100.

mobile ownership offers little explanation of automobile utilization in the 1974 sample.

The ANOVA results given in Table 4 show that the variance explanation by the household-size main effect has also decreased in 1974. Furthermore, the two-way classification scheme based on automobile ownership and household size does not appear as effective in 1974 as in 1963. The large increases in the percentage of the error variance given in Table 3 imply that the variance explained by these two factors has substantially decreased in the 1974 sample. For example, automobile ownership and household size explained 12.42 percent of the total variation in number of trips in the 1963 sample and only 2.78 percent in 1974. This analysis leads to the conjecture that the frequently practiced procedure of trip generation analysis that cross-classifies households according to automobile ownership and household size may not be as effective as it is generally believed to be.

FURTHER EXAMINATION OF DIMINISHING AUTOMOBILE-OWNERSHIP EFFECTS

The apparent decrease in automobile-ownership effects found in the two-way cross-classification analysis of the previous section is reexamined in this section. The intent is to base the conclusion on a more robust statistical basis by conducting further analysis in less restrictive contexts using different statistical models. Two methods used in this section are the log-linear model of classification table analysis *(18)* and analysis of variance with a covariate. In the analysis of this section households are characterized by number of adults, number of workers, life-cycle stage, and automobile ownership.

One of the advantages of the log-linear model of classification table analysis is its liberal cell sample-size requirements, which are crucial when a multidimensional table defined by strongly correlated factors is analyzed. The model is applied to five-way tables formed by categories of automobile ownership (C), number of adults (A), number of workers (W), life-cycle stage (L), and a travel pattern indicator (T). The magnitude of the association between a household attribute and travel indicator can be evaluated by examining the magnitude of the interaction terms involving the two factors. For example, the automobile ownership effect on travel patterns is represented by the interaction term of automobile ownership and the travel indicator, denoted by CT.

This analysis was conducted for three travel indicators: the total number of household trips, the number of driver trips, and the total travel time expenditure. Table 5 gives the magnitude of interaction terms as chi-square statistics divided by the degrees of freedom (to account for the difference in degrees of freedom among interaction effects). The data in the table show a ratio obtained by dividing the chi-square measure for the interaction effect involving each household attribute by the value of the chi-square measure of the interaction involving the number of adults (AT). This ratio is developed so that the 1963 and 1974 samples of different sizes can be compared.

TABLE 5 RELATIVE MAGNITUDE OF THE ASSOCIATION OF HOUSEHOLD ATTRIBUTES AND TRAVEL INDICATORS

	AT	WT	LT	CT
No. of trips				
1963				
χ^2/DOF	10.11	60.07	34.63	81.51
Ratio	1.00	5.94	3.42	8.06
1974				
χ^2/DOF	3.20	8.41	10.89	9.84
Ratio	1.00	2.63	3.40	3.07
Total travel time expenditure				
1963				
χ^2/DOF	9.50	62.30	25.05	51.29
Ratio	1.00	6.56	2.64	5.40
1974				
χ^2/DOF	3.35	4.51	8.67	9.48
Ratio	1.00	1.34	2.59	2.83
No. of driver trips				
1963				
χ^2/DOF	7.94	31.46	18.27	383.10
Ratio	1.00	3.96	2.30	48.24
1974				
χ^2/DOF	2.59	12.30	3.96	25.73
Ratio	1.00	4.76	1.53	9.95

Note: The magnitude of the association between a household attribute and travel pattern indicator is expressed by a chi-square value divided by the degrees of freedom (χ^2/DOF). A refers to the number of adults, W to the number of workers, L to life-cycle stage, and T to travel indicator; AT represents the interaction between A and T and so forth. The relative magnitude of these effects is shown in the table as the ratio to that of AT. The categories used are 1, 2, and 3 or more for number of adults; and 0, 1, and 2 or more for number of automobiles and number of workers. The five life-cycle stages are as defined in Table 1. The effects are all significant at $\alpha = 0.0001$.

The declining relative effect of automobile ownership (CT) in 1974 is evident from Table 5. For example, the automobile-ownership effect on number of trips (CT) in 1963 is more than 8 times larger than that of number of adults (AT). This ratio reduces to 3.07 in the 1974 sample. Although the automobile-ownership interaction term (CT) is always significant (at $\alpha = 0.01$ percent), its relative effects have decreased in 1974 for all three travel pattern indicators examined in Table 5; it is no longer a predominant factor for number of trips or travel time expenditure.

Analysis of variance (ANOVA) is next applied to the same multidimensional classification table. Two modifications to the table were necessary because of sample-size requirements. First, the number of workers became a covariate, rather than a classifier (it is assumed that the covariate has an identical slope for all household subgroups). Second, automobile ownership had to be represented by the following two categories: no-car households and households with one or more cars for the 1963 sample, and households with zero or one car and multicar households for the 1974 sample because of the small number of no-car households in the 1974 sample. The first change appears to have resulted in an overrepresentation of the effects of number of workers, and the second change may possibly have caused an underrepresentation of automobile-ownership effects.

This ANOVA was conducted on the following set of travel indicators: number of trips, driver trips, passenger trips, automobile trips, trip chains, trips for work, social-recreational trips, maintenance trips, and trips to serve passengers as well as travel time expenditure. The results of this ANOVA, given in Table 6, indicate the same decline in variance explanation by household automobile ownership. The decline is especially noticeable for number of driver trips, number of car trips, and total driver–trip time expenditure—the same result found in the simpler analysis of Table 4. Although the analysis here is limited by the binary categorization of automobile ownership, the consistency found between the data in Tables 4 and 6 supports the conclusion of diminishing effects of automobile ownership on travel.

Only a few of the ANOVA tables of Table 6 exhibit appreciable differences in the total variance explained between 1963 and 1974. For some travel pattern indicators (e.g., total number of trips), the variance explanation increases (and the error variance decreases) for the 1974 sample. This forms a marked contrast to the result shown in Table 4, where the ANOVA based on cross-classification by household size and automobile ownership indicated that the percent of variance explained by these two factors sharply decreased in 1974 for all indicators examined. The data in Table 6 thus offer additional support of the conjecture that the cross-classification of households according to automobile ownership and household size may not be as effective a tool for trip generation analysis as it has been believed to be.

The same analysis of variance is repeated for the subgroup of households that are in later stages of life cycle, namely, those households whose heads are at least 45 years old and where no children are present. This particular subgroup is studied here partly because its internal sample distribution allows the application of the three-category representation of automobile ownership (no-car, single-car, multicar). An analysis of variance of this group of households can therefore be used to confirm the diminishing automobile-ownership effects found in Table 6. Analyzing this group is also useful because its lower automobile-ownership rate as indicated in the previous analysis (*12* and Table 1) may imply different automobile-ownership effects for this group. The results are given in Table 7 in the same format as in Table 6, except that life-cycle stage is no longer a classifier. The ANOVA tables in general confirm the earlier results with the automobile-ownership main effect dropping dramatically between the two years for all twelve of the indicators. The conjecture of diminishing automobile-ownership effects holds true for households of later life-cyle stages as well as for nuclear-family households *(12)* and all households examined collectively.

TABLE 6 ANALYSIS OF VARIANCE OF LIFE CYCLE, NUMBER OF ADULTS, AND AUTOMOBILE OWNERSHIP EFFECTS ON HOUSEHOLD TRAVEL PATTERNS

	Effect (degrees of freedom)								
	L (4)	A (2)	C (1)	LA (8)	LC (4)	AC (2)	LAC (8)	W (1)	Error
No. of trips									
1963	**1.91**	**0.29**	**3.14**	0.03	**0.34**	**0.16**	0.05	**2.48**	91.59
1974	**4.68**	0.13	0.36	0.25	0.39	0.04	0.63	**3.94**	89.59
No. of driver trips									
1963	**0.34**	0.05	**8.60**	0.04	**0.66**	**0.35**	0.03	**1.87**	88.05
1974	**1.02**	0.13	**0.81**	0.34	0.25	0.12	0.41	**5.49**	91.43
No. of passenger trips									
1963	**1.42**	**0.17**	**0.39**	0.06	0.11	0.09	0.09	**0.47**	97.20
1974	**3.46**	0.22	0.01	0.43	0.30	**0.74**	1.17	**0.62**	93.05
No. of automobile trips									
1963	**1.04**	**0.12**	**4.64**	0.03	**0.45**	**0.36**	0.07	**1.49**	91.79
1974	**2.50**	0.12	**0.39**	0.27	0.36	**0.04**	0.68	**4.16**	91.48
Travel time expenditure									
1963	**1.22**	**0.33**	**0.72**	0.06	0.04	0.05	0.06	**2.43**	95.11
1974	**1.44**	0.04	0.40	0.21	0.52	0.02	0.29	**1.02**	96.06
Total driver trip time									
1963	0.11	0.07	**6.17**	0.02	**0.30**	**0.39**	0.04	**1.67**	91.22
1974	0.30	0.05	**0.42**	0.24	0.43	0.09	0.21	**1.10**	97.16
No. of trip chains									
1963	**2.56**	**0.56**	**3.24**	0.03	**0.41**	**0.17**	0.07	**2.35**	90.61
1974	**5.05**	**0.43**	**0.39**	0.19	0.29	0.02	0.45	**3.87**	89.30
No. of work trips									
1963	0.04	0.00	0.27	0.05	0.01	0.03	0.04	**25.18**	74.37
1974	0.16	**0.44**	0.15	0.67	0.28	0.21	0.37	**23.09**	74.64
No. of joint nonwork trips									
1963	**0.80**	**0.13**	**1.03**	0.07	**0.20**	0.08	0.04	**0.15**	97.51
1974	**1.81**	**0.63**	0.02	0.66	0.28	**0.69**	1.12	0.21	94.57
No. of maintenance trips									
1963	**0.60**	**0.25**	**1.61**	0.03	0.12	**0.14**	0.09	**0.20**	96.95
1974	**1.75**	**0.67**	0.03	**1.42**	0.34	0.23	0.88	0.21	94.46
No. of social-recreational trips									
1963	**1.00**	0.08	**0.69**	0.09	0.06	0.03	0.04	0.01	98.00
1974	0.65	0.19	0.00	0.58	0.48	**0.04**	1.03	0.04	96.98
No. of serve-passenger trips									
1963	0.18	0.01	**1.43**	0.04	**0.25**	0.09	0.03	**0.76**	97.21
1974	0.50	0.37	0.00	0.82	0.15	0.03	0.22	**0.91**	96.99

Note: Number of workers is used as a covariate in this analysis of variance. The categories used are 1 adult, 2 adults, and 3 or more adults for number of adults (A) and the five stages for life-cycle stage (L) are as defined in Table 1. Because of sample size limitations, different automobile-ownership categories are used in the two survey years: 0 automobile and 1 or more automobiles for 1963, and 0 or 1 automobile and 2 or more automobiles for 1974. The degrees of freedom for the error terms are 7,059 in 1963 and 1,576 in 1974. Interaction terms significant at $\alpha = 0.01$ are indicated by bold-faced numbers. All rows total 100.

TABLE 7 ANALYSIS OF VARIANCE OF NUMBER OF ADULTS AND AUTOMOBILE OWNERSHIP EFFECTS ON HOUSEHOLD TRAVEL PATTERNS: OLDER HOUSEHOLDS

	Effect (degrees of freedom)				
	A (2)	C (2)	AC (4)	W (1)	Error
No. of trips					
1963	**0.40**	**4.51**	**0.50**	**11.25**	83.33
1974	1.24	0.95	1.17	**5.13**	91.51
No. of driver trips					
1963	0.11	**8.79**	0.20	**6.20**	84.71
1974	0.78	**1.61**	1.05	**6.05**	90.52
No. of passenger trips					
1963	**1.54**	**1.13**	**1.34**	**2.24**	93.75
1974	0.80	0.03	1.36	0.30	97.51
No. of automobile trips					
1963	0.18	**6.80**	**0.71**	**6.56**	85.76
1974	1.17	0.96	1.33	**5.15**	91.39
Travel time expenditure					
1963	0.22	**2.10**	0.41	**5.94**	91.34
1974	0.46	0.68	0.71	0.39	97.76
Total driver trip time					
1963	0.07	**7.51**	0.27	**2.63**	89.52
1974	0.19	0.87	0.69	0.47	97.78
No. of trip chains					
1963	**1.28**	**4.43**	**0.98**	**9.73**	83.58
1974	**1.56**	**1.43**	1.53	**4.80**	90.68
No. of work trips					
1963	**0.33**	**0.88**	**0.31**	**40.83**	57.65
1974	0.25	0.04	0.04	**39.89**	59.77
No. of joint nonwork trips					
1963	**0.90**	1.45	**1.51**	**0.39**	95.75
1974	**1.72**	0.11	1.35	**2.33**	94.49
No. of maintenance trips					
1963	0.31	**2.16**	0.34	0.07	97.12
1974	0.60	0.75	0.47	**1.22**	96.95
No. of social-recreational trips					
1963	0.27	**1.65**	0.25	**0.26**	97.58
1974	0.89	0.21	1.10	**1.64**	96.16
No. of serve-passenger trips					
1963	0.13	**1.33**	0.42	**3.02**	95.10
1974	0.67	0.04	0.39	0.19	98.71

Note: This tabulation includes the household life-cycle stage 5 (head's age no less than 45 years, no children). Number of workers is used as a covariate. The categories used are 0, 1, and 2 or more for number of automobiles and 1, 2, and 3 or more for number of adults. Bold-faced numbers are significant at $\alpha = .01$. All rows total 100.

SUMMARY AND CONCLUSIONS

The earlier analysis of 1963 and 1974 nuclear-family households indicated that the effect of automobile ownership on trip rate, travel time expenditure, and activity engagement is diminishing. This study broadens this finding to include households of all types.

Examination of the trip rates of all of the households in the 1963 and the 1974 samples shows that, although trips per person did not change much over the 11 years between the two surveys, the trips per automobile decreased considerably, which indicates that households with lower propensity to travel were joining multicar households. Furthermore, the difference between the trip rates of one-car and multicar households, which was clear in 1963, was much less discernible in 1974. The variance explanation of automobile ownership on total driver time, which is a reasonable surrogate for vehicle miles traveled by the household, was approximately 10 percent in 1963 and decreased to only 1 percent in 1974.

Three different analyses, ANOVA using automobile ownership and household size as classifiers, a log-linear model of multidimensional classification table analysis, and a multidimensional ANOVA with a covariate, the last two of which used more extensive household composition classifications, found large decreases in the association of automobile-ownership classifications and travel pattern indicators. This was true for all of the households in the sample examined collectively and also for households in later stages of life cycle.

The analysis of this study also indicates that the effectiveness of the cross-classification analysis based on automobile ownership and household size in household trip generation analysis has decreased substantially. The variance in household trip generation explained by this cross-classification scheme decreased from 12 percent in 1963 to 3 percent in 1974. When household size was replaced with a more extensive descriptor of household composition, the variance explained by the descriptor together with automobile ownership was about 10 percent in both years. The result implies that household size is no longer an adequate descriptor of household composition, which presumably has more direct and stable association with household travel patterns.

This analysis has consistently indicated that automobile ownership and household size are not as effective classifiers in household travel demand analysis as they are generally believed to be. It is difficult to challenge such a widely practiced household trip generation procedure as the cross-classification by automobile ownership and household size. However, when this classification scheme was being developed and when automobile ownership was indeed strongly associated with travel behavior, this country was in earlier stages of motorization. If automobile-ownership effects have been changing with motorization, it is probable that trip generation procedures have been established on the basis of transient relationships. The results of this study urge a fundamental and critical review of the existing trip generation procedures.

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REFERENCES

1. J. D. Carroll. *Detroit Metropolitan Area Traffic Study*. Detroit, Mich. 1955.
2. *Trip Generation Analysis*. Urban Planning Division, FHWA, U.S. Department of Transportation, 1975, 150 pp.
3. T. J. Tardiff. "Perception of the Availability of Transportation Alternatives for Various Trip Purposes." In *Transportation Research Record 592*, TRB, National Research Council, Washington, D.C., 1976, pp. 12–16.
4. J. Berechman and R. E. Paaswell. Impact of Car Availability on Urban Transportation Behavior. *Transportation*, Vol. 6, 1977, pp. 121–34.
5. H. S. Levinson. "Urban Travel Characteristics." In *Transportation and Traffic Engineering Handbook* (J. E. Baerwald, ed.), Prentice-Hall, Englewood Cliffs, N.J., 1976, pp. 138–206.
6. B. G. Hutchinson. *Principles of Urban Transport Systems Planning*. McGraw-Hill Book Co., New York, 1974.
7. D. L. Ochoa and G. M. Ramsey. *The 1976–1980 Statewide Travel Survey*. Division of Transportation Planning, California Department of Transportation, Sacramento, 1981.
8. H. J. Wootton and G. W. Pick. A Model for Trips Generated by Households. *Journal of Transport Economics and Policy*, Vol. 1, 1967, pp. 137–153.
9. *Historical Statistics of the United States, Colonial Times to 1970*. Bureau of the Census, U.S. Department of Commerce, Part 2, 1975.
10. *Statistical Abstract of the United States: 1984*. 104th ed. Bureau of the Census, U.S. Department of Commerce, 1983.
11. B. Horn and R. Matthews. "International Trends in Car Ownership and Prospects for the Future in OECD Member Countries." Presented at 62nd Annual Meeting of the Transportation Research Board, Washington, D.C., 1983.
12. R. Kitamura and L. P. Kostyniuk. Maturing Motorization and Household Travel: The Case of Nuclear-Family Households. *Transportation Research*, Vol. 20A, No. 3, 1986, pp. 245–260.

13. "Rochester Metropolitan Transportation Study." In *The 1990 Transportation Plan*, Planning Division, New York Department of Transportation, Albany, 1969.
14. D. T. Hartgen and J.T. Knoll. *Design for the Genesee Transportation Study Travel Survey, Fall 1974*. Preliminary Research Report 64. Planning Research Unit, New York State Department of Transportation, Albany, 1974.
15. R. Kitamura, L. P. Kostyniuk, and M. J. Uyeno. "Basic Properties of Urban Time-Space Paths: Empirical Tests." In *Transportation Research Record 794*, TRB, National Research Council, Washington, D.C., 1981, pp. 8–19.
16. L. P. Kostyniuk and R. Kitamura. "Life Cycle and Household Time-Space Paths: Empirical Investigation." In *Transportation Research Record 879*, TRB, National Research Council, Washington, D.C. 1982, pp. 28–37.
17. L. P. Kostyniuk and R. Kitamura. Temporal Stability of Urban Travel Patterns. *Transportation Policy and Decision Making*, Vol. 2, 1984, pp. 481–500.
18. S. E. Fienburg. *The Analysis of Cross-Classified Categorical Data*. Massachusetts Institute of Technology Press, Cambridge, 1977.

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Availability of Information and Dynamics of Departure Time Choice: Experimental Investigation

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The effect of information availability on the dynamics of user behavior in urban commuting systems is investigated through an experimental procedure that involves real commuters interacting in a simulated traffic system under two distinct informational situations: in one only the decision maker's own performance on the previous day is available, and in the other complete information about the system's performance on the previous day is available. The results are examined from the perspective of a theoretical framework articulated previously in conjunction with the results of the first, limited-information, experiment. The focus of this paper is on the results of the complete-information experiment relative to those obtained in the first one. It is found that additional information raises users' aspiration levels and generally improves their predictive capability, but results in greater day-to-day departure time switching and longer convergence periods to a steady state, which is superior, in terms of user costs, to that attained under limited information.

The dynamics of individual choice behavior in transportation systems remain one of the least understood aspects of travel demand analysis. Of particular interest are the dynamics of trip-timing decisions, which determine the time-varying flow patterns in commuting systems and are important elements in the design and evaluation of peak-period congestion relief strategies. A major source of complexity in addressing these phenomena is the dynamic interaction between user decisions and the system's performance, which greatly diminishes the ability of conventional survey methods to generate observational data at a meaningful level of richness within practical resource constraints.

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Recently, a promising experimental approach was proposed by Mahmassani et al. *(1)*, whereby real commuters were involved during a period of 24 days in a simulated traffic system. The consequences of individual departure time decisions on a given day were evaluated by simulating traffic patterns in the system resulting from the aggregated time-varying departure functions. Given feedback from the simulation, participants would select their departure time for the next day. This approach provides a useful alternative to prohibitive large-scale, real-world experiments for studying the commuting system's overall behavior and dynamic properties as well as the behavioral mechanisms that govern the day-to-day choices of individual trip makers. In particular, it can effectively support theoretical development and model building, which could be subsequently validated, if only in part, in the field.

One of the attractive features of this approach is that it affords the analyst a high degree of control over the information available to participants, thereby allowing the investigation of the effect of availability of information on the system's dynamic properties. In the first such experiment conducted *(1, 2)*, the informational situation considered was one in which users had only their own experience to rely on. Everyday, participants were provided with their performance on the previous day, in the form of an arrival time at the work destination.

A theoretical framework for the day-to-day departure time decision-making dynamics of individual commuters was presented by Mahmassani and Chang *(2)*, along with the results of that first experiment. The principal behavioral hypothesis were subsequently verified through the calibration of individual choice models *(3, 4)*. In particular, user behavior under limited information in the commuting system was viewed as a dynamic boundedly rational search for an acceptable departure time. The acceptability of a given departure time ($DT_{i,t}$) for user i on day t and the resulting arrival time ($AT_{i,t}$) are determined relative to some "aspiration level," according to Simon's well-known "satisficing" decision rule *(5)*. Specifically, the notion of an "indifference band" of tolerable schedule delay [defined as the difference between user i's preferred arrival time (PAT_i) and actual arrival time ($AT_{i,t}$)] was introduced as the principal acceptability mechanism. The dynamic variation of this indifference band and its generally increasing response to unsuccessful experience with the facility's performance was established, reflecting a downward revision of aspiration level *(2, 3)*.

The role of information and the nature and degree of its availability in this framework are essential in determining user behavior and therefore in influencing the dynamics of the entire traffic commuting system. Information operates on two key behavioral processes: (*a*) perception and learning about the facility's performance, which ultimately determine user actions, in the form of departure time adjustments, and (*b*) aspiration level revision, as previously mentioned. Information can come from two principal sources in this context: the decision maker's own experience with the facility; or exogenous sources, such as media traffic reports, word of mouth, and so on, which are of particular concern to information-related congestion control policies; or a combination of the two sources. In the first experiment, only the first source was available to participants. This prevented the assessment of the effect of information, because only one level of this experimental factor was employed.

A second experiment was therefore conducted, under the same conditions as the previous one except for the informational situation, in which participants were provided with a complete profile of the system's performance on the previous day. The details are given in the next section.

In this paper is presented a comparative analysis of the two experiments, focusing on the effect of information on (*a*) the system's overall behavior, particularly convergence to an equilibrium and the patterns of this evolution, and (*b*) the processes governing the choice dynamics of individuals. The analysis parallels that presented previously for the first experiment *(2)* and is therefore essentially exploratory in nature. It is aimed at developing the principal insights and hypotheses that would be subsequently addressed through more formal and elaborate econometric analysis.

EXPERIMENTS

None of the participants in the second experiment had taken part in the first one, thereby controlling for initial bias and learning effects. This is also part of the reason for which two experiments were required instead of a single one during the course of which the informational situation would be changed. Such alternative experimental designs include changing availability of information for all or only some participants (*a*) after convergence is achieved under one level, (*b*) at prespecified intervals during the experiment, or (*c*) at random. However, such designs would unduly confuse participants, diminish their goodwill, and generally reduce the realism of the situation, in addition to increasing the difficulty of analyzing and interpreting the experimental results.

The details of the first experiment are described elsewhere *(1, 2)*. The second one followed essentially the same procedure, including the commuting context, which consisted of a single highway facility (two lanes in each direction, access limited to a finite number of entry points) and adjoining residential sectors. All commuters must use the facility to travel to their common destination, such as a city's central business district (CBD) or a major suburban industrial park. The commuting corridor is subdivided into nine 1-mi sectors, with the common destination located at the end of the last sector (number 9, because sectors are numbered from 1 to 9 in decreasing order of distance from the destination). Only the first five sectors were designated as residential, and there was no traffic generation from the remaining sectors.

One hundred participants, all working staff at the University of Texas at Austin, were carefully selected and assigned equally to the five residential sectors. The selection process made it extremely improbable for direct communication to take place among participants, thereby precluding cooperative behavior and controlling for availability of information. Participants were given a description of the commuting situation and instructed that they needed to be at work by 8:00 a.m., with the stipulation that no late arrival at the workplace was tolerated, which is not very different from their own working conditions. The identical work start time and no lateness conditions were imposed in order to eliminate nonessential complication in the interpretation of the results and to keep the number of participants at a manageable level while allowing a meaningful level of interaction to develop in the traffic system.

The procedure can be summarized as follows:

1. Supply each participant i, $i = 1, \ldots, 100$, with initial information and instructions.
2. On day t, all participants supply their departure time decisions ($DT_{i,t}$); these are aggregated by sector into time-dependent departure functions [$N_{k,t}(T)$] where T is the time of day, $k = 1, \ldots, 5$.
3. The departure functions are input to a special-purpose macroparticle traffic simulation model [or MPSM, described in detail elsewhere *(6)*], which yields the respective arrival times ($AT_{i,t}$), travel times ($TT_{i,t}$), and other pertinent traffic performance measures. Note that each participant was treated as 20 trip makers making identical decisions for traffic simulation purposes.
4. If steady state is established, or a maximum experiment duration is reached, stop; otherwise, set $t = t + 1$, supply each participant with information on actual performance on the preceding day, and go to Step 2 for updated departure time decisions from the participants.

It is in this last step that the two experiments are different. As mentioned earlier, only $AT_{i,t-1}$ was provided to participant i on day t in the first experiment. However, in the second experiment, each participant was supplied with the arrival times corresponding to an array of possible departure times between 7:00 a.m. and 7:50 a.m., in 5-min increments, from that participant's origin sector. Note that the 5-min increments were chosen on the basis of the earlier observation that participants appeared to naturally select departure times in this manner *(1, 2)*. The information was presented in the form of "if you had left at 7:15, you would have arrived at 7:40." Therefore, trip makers essentially had complete information about the travel time performance of the facility for departures from their origin sector on the preceding day. Naturally, in an evolving system, there was no guarantee that this pattern would be maintained on the next day.

EXPERIMENTAL RESULTS

The following questions are addressed in this presentation of the experimental results: (*a*) initial preferences, (*b*) convergence and system performance, and (*c*) behavioral processes.

Initial Preferences

It has been shown in previous work that the state to which a given commuting system converges, if at all, as well as the evolutionary path toward such a state, depend on the initial conditions of the system (*7*). Similar conclusions were reached by Horowitz in the somewhat different context of stochastic route choice in a two-link network (*8*). In the present experiments, all initial elements except the actual participants were identical, including the initial information supplied to participants. As discussed earlier, it is neither practical nor desirable to use the same participants in the two informational situations nor to employ more complicated experimental designs.

Initial preference was found to be a key factor in explaining differences in the dynamics of user behavior in the first experiment. It is captured in these experiments by the preferred arrival time (PAT_i) supplied by each participant at the beginning of the experiment. This quantity is generally different from the actual work start time (note that $PAT_i \leq WS$) and reflects inherent differences of individual tastes and preferences, as well as an indication of a user's attitude toward risk. As before, it serves as a basis for segmenting the participants into three groups: (*a*) Group 1, which includes all users i such that 7:30 a.m. $\leq PAT_i <$ 7:40 a.m.; (*b*) Group 2, for whom 7:40 a.m. $\leq PAT_i <$ 7:50 a.m.; and (*c*) Group 3, for whom 7:50 a.m. $\leq PAT_i <$ 8:00 a.m.

Comparisons of the distribution of participants in these groups across sectors (within the same experiment) and between the two experiments were performed using chi-square tests. No systematic variation across sectors could be detected in either case. More significant, the hypothesis that this distribution is the same for the two different sets of participants could not be rejected at the 10 percent significance level. This is indeed a remarkable result that provides a stronger basis for comparing the results of the two experiments. Because the initial conditions can be considered to be essentially the same in both cases, differences in the dynamics of the system can be more clearly attributed to the effect of the availability of information.

Convergence and System Performance

Four questions are of concern here:

1. Does the system converge to a steady state?
2. How long does it take to do so?
3 What temporal and spatial patterns can be distinguished in the system's evolution under each informational situation?
4. Does it converge to the same state in both experiments? How do the two equilibria differ (in terms of user costs)?

Convergence in these experiments has been defined in terms of the departure patterns from each sector. When all users stop adjusting their departure times, steady state is reached. Because the traffic simulation is deterministic, all system performance measures associated with a given set of steady-state departure functions also converge. Steady state was reached as of day 20 (for the overall system) in the first, limited information, case, and maintained for 5 days before the experiment was stopped. Steady state was reached as of day 29 in the second case. Note that although only one final day with no switching was observed in the second experiment, the system was considered essentially at steady state because only an insignificant amount of switching had been taking place during the preceding 5 days. The total duration of the second experiment was therefore 6 weeks (5 days per week).

The first striking result is that the system takes longer to converge under complete information than when users are provided with only their own preceding day performance. This is true in all sectors, as indicated by the data in Table 1, which gives the time until convergence in each sector under both informational situations. Because this time could be unduly affected by a small number of persisting participants, it is useful to examine the day-to-day evolution of the fraction of users who change departure time, shown in Figure 1 for Sectors 1–5, respectively, for each experiment. Table 2 gives a further summary of this information by listing the number of days of each experiment on which at least 25, 50, and 60 percent, respectively, of users in each sector change their departure time. This provides a more meaningful comparison across sectors and between experiments because it captures the intensity of switching activity in each sector. The conclusion that it takes longer for each sector to converge under the complete-information situation than under the limited-information one is clearly borne out by the results.

TABLE 1 TIME, IN DAYS, UNTIL CONVERGENCE IN EACH EXPERIMENT, BY SECTOR

	Sector				
Experiment	1	2	3	4	5
1	21	18	17	17	5
2	27	27	29	22	18

Particularly noteworthy is the substantially greater difficulty of convergence exhibited by Sectors 2–5 in the second experiment relative to the first, as revealed by the switching frequency data. It can also be noted that Sectors 2 and 3 exhibit even greater difficulty than Sector 1 in the second experiment, unlike the situation in the first experiment, in which sectors closer to the destination converged sooner than more distant ones (*1*). This apparent difference in the spatial pattern of the system's evolution is a manifestation of a more fundamental result that holds in both cases. Namely, sectors in which residents encounter greater day-to-day fluctuations in system performance require a longer time to converge (and will experience more intense switching activity in the process). In the first experiment, more distant sectors exhibited greater day-to-day fluctuations than closer ones. In the second, Sector 3 had by far the most drastic fluctuations, as shown in Figures 2 and 3 that depict the day-to-day evolution of the average (of the absolute value of) schedule delay and travel time, respectively, experienced by users in each sector [these can be contrasted with similar figures for the first experiment given elsewhere (*2*)].

The fluctuation pattern in a given sector is a result of the complex interaction of decisions made by users in all sectors and

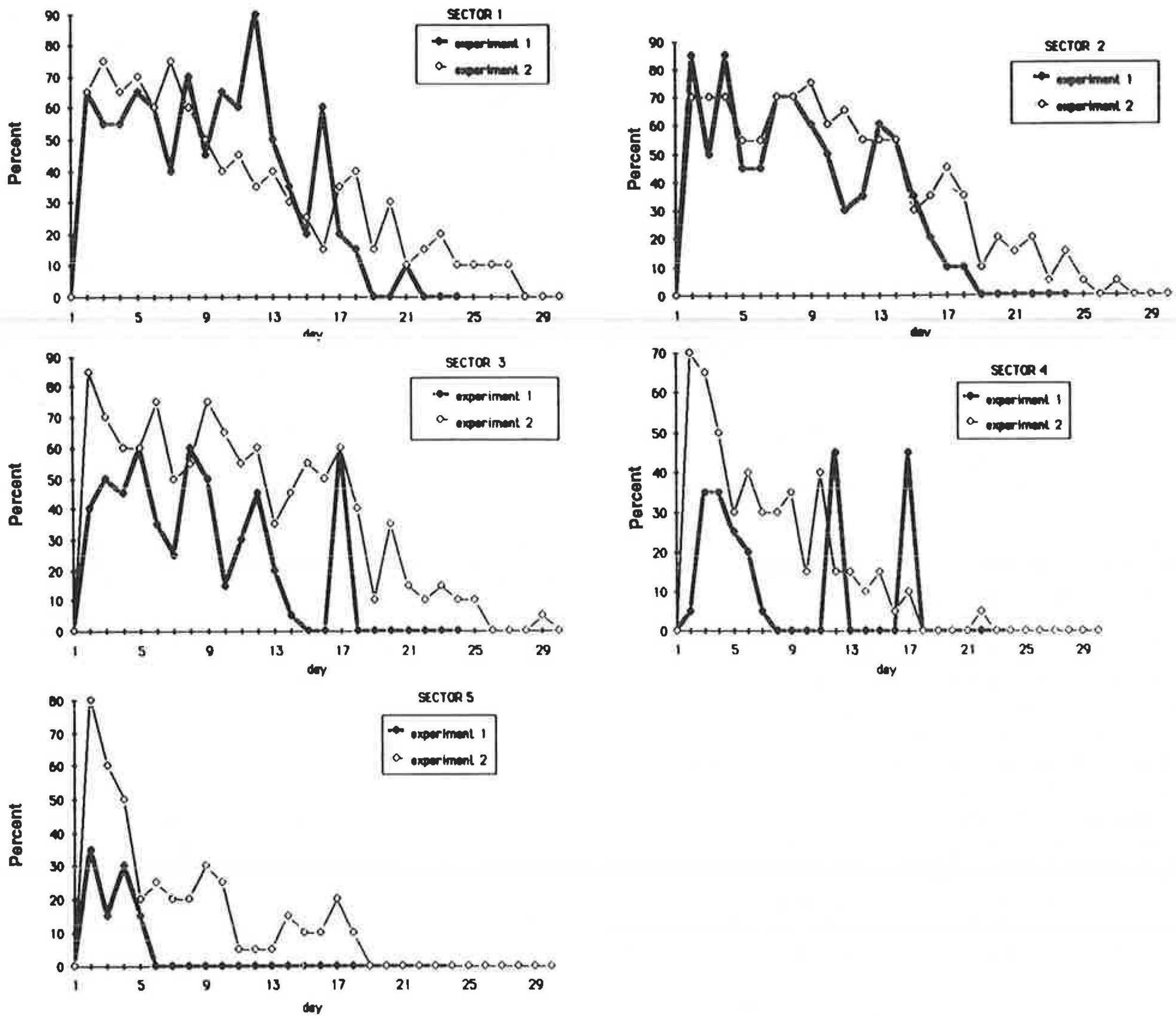


FIGURE 1 Day-to-day evolution of the fraction of users who change departure time in each experiment, by sector.

TABLE 2 NUMBER OF DAYS OF EACH EXPERIMENT WITH AT LEAST 25, 50, AND 60 PERCENT OF USERS CHANGING DEPARTURE TIME, BY SECTOR

Fraction Changing (%)	Experiment	Sector 1	2	3	4	5
≥25	1	14	14	11	5	2
	2	17	17	18	9	6
≥50	1	11	9	5	0	0
	2	8	13	14	3	3
≥60	1	7	6	2	0	0
	2	7	8	9	2	2

cannot be predicted. Evidently, there is a higher degree of interaction when users are provided with more information, which is reflected in the longer convergence times for each sector. At this stage, a possible explanation is that users have greater expectations when provided with more information and may therefore have a greater willingness to experiment. However, a traffic commuting system such as the one in question is a highly nonlinear interactive system in which the travel time profile on day $t - 1$ may be a misleading predictor for travel time on day t. In other words, it is not clear that users, no matter how sophisticated they might be, can process and integrate the provided information to accurately predict system performance. These questions will be addressed to a greater extent later in this paper in conjunction with the discussion of users' behavioral mechanisms.

It can further be noted in Figures 2 and 3 that, despite the continuing fluctuation of schedule delay and travel time, users in sectors already in steady state (particularly Sectors 4 and 5) maintained their departure decisions. This was observed in both experiments and is consistent with what can be expected under boundedly rational behavior and the associated "indifference band" notion described in the first section *(2, 3)*.

The steady-state schedule delay and travel time shown in Figures 2 and 3 are contrasted in Figure 4 with those obtained under the limited-information situation. This figure consists of a scatter plot in the schedule delay-travel time space of the steady-state performance of each sector under the two experiments, thereby making it possible to compare and assess the states to which the system converged under the two informational situations. It is clear from the steady-state departure distributions and all other

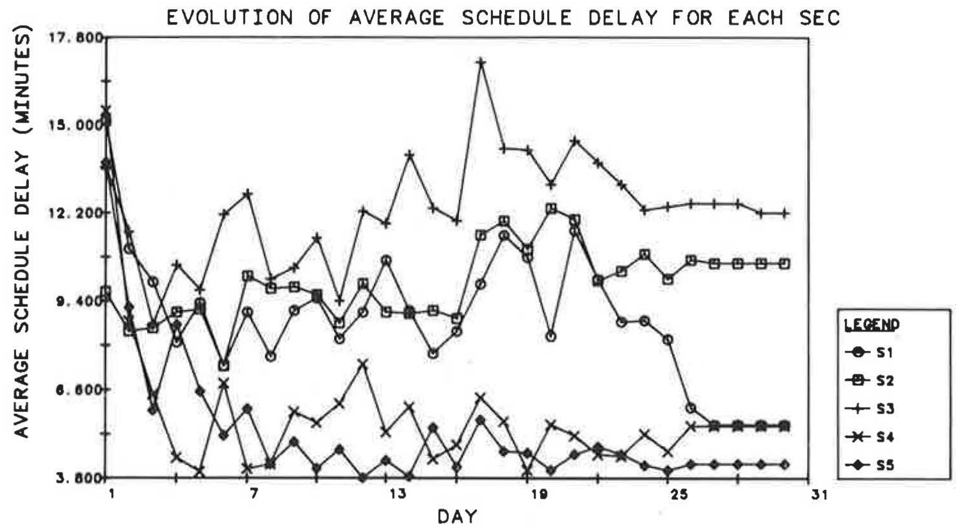


FIGURE 2 Day-to-day evolution of the average absolute schedule delay for each sector, Experiment 2.

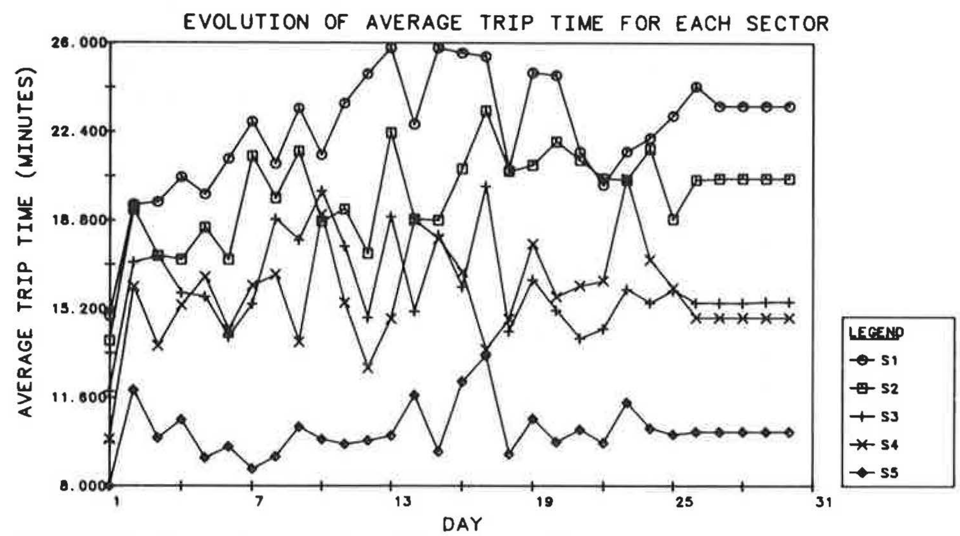


FIGURE 3 Day-to-day evolution of the average trip time for each sector, Experiment 2.

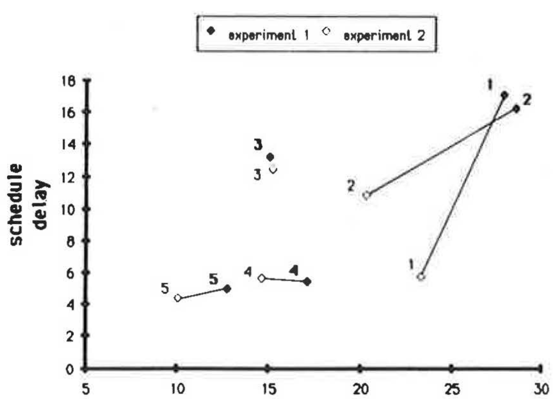


FIGURE 4 Comparative steady-state performance of each sector under the two informational situations.

associated performance measures that the two states are quite distinct. Therefore, despite identical system elements and similar initial preferences of participants, two different equilibria were reached. This nonuniqueness is consistent with the results, derived by Mahmassani and Chang for an idealized situation *(9)*, regarding the properties of boundedly rational user equilibrium (BRUE). The latter is attained in a system when all users have accepted their current outcome and no longer desire to change decisions. Similar results were also obtained in a number of computer simulations with endogenously specified commuter decision rules *(7)*.

Figure 4 also permits the assessment of how the two equilibria compare in terms of user costs (or components thereof). The conclusion is once again striking: overall, users are better off under the second informational situation. This is particularly true for Sectors 1 and 2, where quite significant reductions of about 67 and 33 percent, respectively, in average schedule delay, and 16 and 29 percent, in average trip time, were observed. Sector 3, which took the longest to converge in the second experiment, experienced virtually no improvement, with a slight decrease in schedule delay and about the same average trip time. Sector 4 exhibited a decrease in average trip time of about 15 percent and a slight increase in schedule delay.

The overall picture that emerges from the comparisons is that providing uses with more complete information about the system's performance has induced higher aspiration levels and allowed users to ultimately attain a better equilibrium state. However, given the difficulty of learning and prediction in a system with the kind of nonlinear interactions present here, users switched with greater frequency, which resulted in longer times until convergence. User behavior is further explored hereafter.

User Behavior

Following the presentation *(2)* of the results of the first experiment in which users were supplied with their own previous performance only, user actions, intentions, and perceptions and learning are examined in turn.

Actions

The evolution of the fraction of users who change departure time in each sector was seen earlier. This is examined further through the distribution of the number of departure time changes across users in the various sectors. In the first experiment, this frequency increased with distance from the destination and exhibited a marked dependence on users' initial preference group; users with earlier initial preferred arrival time (e.g., Group 1) have to change actions less frequently than do those with a later *PAT*.

Table 3 gives the same information for the second experiment, showing the fraction of users in each sector who changed their departure time at least n times, where $n = 1 \ldots, 23$ (highest number of changes observed). Figure 5 shows that information on a *PAT* group basis within each sector. Overall, all sectors experience greater switching frequency under the complete-information situation, which is consistent with the results of the previous section. The same general trends as before are still present; first, sectors that experience greater fluctuations of system performance have higher switching frequencies, in particular Sectors 2 and 3. This same principle resulted in the apparent dependence on distance in the first experiment. Regarding the *PAT* group effect, it can be noted that Group 1, consisting of users with the earliest preferred arrival times, exhibits in all sectors the same trend as in the first experiment, with a considerably smaller number of changes than are made by users in the other groups. Groups 2 and 3 are not so well differentiated in terms of switching frequency; this distinction was not particularly strong in the first experiment either.

As was mentioned previously, the mechanism that triggers a departure time change was found under the limited-information experiment to consist of an indifference band of tolerable schedule delay, which increased over time (in the first experiment) as users interacted with the traffic system in their search for an acceptable departure alternative *(2–4)*. Figure 6 shows scatter plots of the magnitude of the departure time adjustment on day t (i.e., $DT_{i,t} - DT_{i,t-1}$) versus $SD_{i,t-1}$, the schedule delay on day $t-1$, for all users in the system, for $t = 2, 6, 11, 16, 21, 26$, and 30 in Experiment 2. Focusing on the evolution of the points corresponding to a zero departure time adjustment, these plots provide a rather effective illustration that (*a*) there indeed exists a range of schedule delay that users are willing to tolerate and (*b*) this range appears to increase over time, reflecting users' acceptance of progressively greater schedule delay. Both conclusions were also evident in similar plots for the first experiment *(2)*.

There are notable differences, however, between the two informational situations. Under complete information, the scatter in the plots of Figure 6 is greater than in the first experiment, particularly

TABLE 3 PERCENTAGE OF USERS, IN EACH SECTOR, WITH AT LEAST *n* DEPARTURE TIME CHANGES

No. of	Sector 1		Sector 2		Sector 3		Sector 4		Sector 5		All Sectors	
Changes	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2
1	100	95	100	100	100	100	100	85	75	90	95	94
2	100	90	100	100	95	100	65	75	25	70	77	87
3	100	90	100	100	90	90	60	70		55	70	81
4	100	90	95	95	85	90	15	55		40	59	74
5	90	90	90	90	70	90	5	45		40	51	71
6	90	80	80	80	40	90		40		30	42	64
7	90	65	75	75	30	75		35		30	39	56
8	80	60	60	70	10	75		30		20	30	51
9	65	45	50	65		65		20		20	23	43
10	50	45	30	50		60		15		5	16	35
11	35	40	15	45		55		5		5	10	30
12	25	35		40		55		5		5	5	28
13	20	35		35		45					4	23
14	10	25		35		40					2	20
15	5	25		20		35					1	16
16		20		20		20						12
17		15		15		5						7
18		10		5		5						4
19				5		5						2
20				5		5						2
21				5								1
22				5								1
23				5								1

Note: Exp. = experiment.

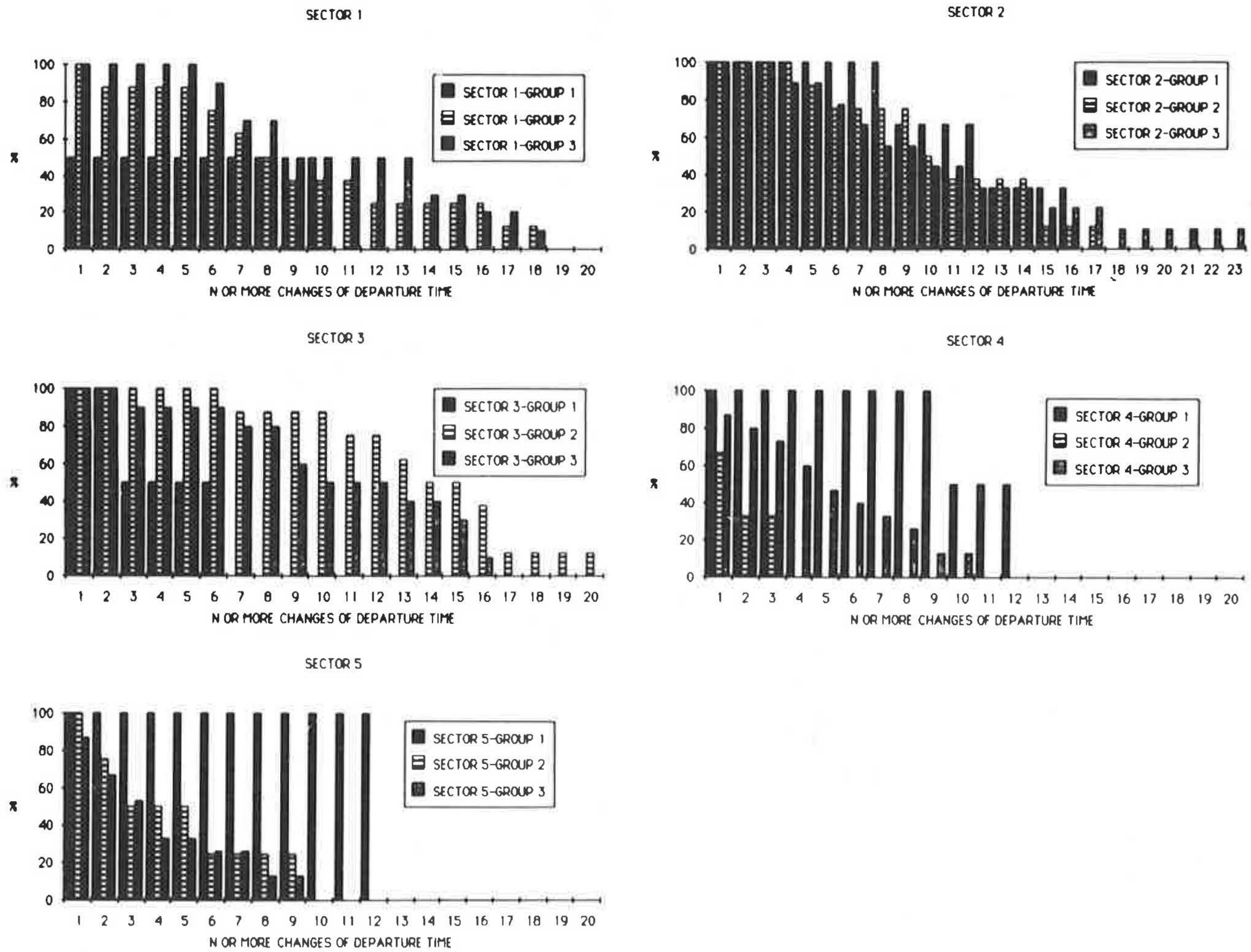


FIGURE 5 Fraction of users in each group with at least *n* departure time changes, by sector, Experiment 2.

during the early stages. This is due to a somewhat less "myopic" adjustment behavior than that observed when users had information about their own performance only. Namely, it was noted then that early arrival (relative to the individual's *PAT*) on day $t - 1$ almost always implied later (or same) departure on day *t*, whereas late arrival implied earlier (or same) departure the next day. This no longer appears to hold when users were provided with more information, as seen in the first two parts of Figure 6. However, as the system evolved, this adjustment pattern became the dominant one, as seen in Figure 6 for day 11 through day 30. A plausible explanation is found in the effect of information on the departure time selection process itself. Under limited information, departure time choice from one day to the next is viewed as an adjustment process anchored in the current decision, whereby a quantity is added to or subtracted from the present departure time, based on the individual's latest experience. When information is provided on all possible alternatives, many users become aware of these other alternatives and may be willing to select the one that has yielded (or that they predict will yield) what they consider to be the best outcome, independently of their current or previous decisions. Therefore, providing information on all alternatives appears to have induced some users to behave in what can be interpreted as a more optimizing manner. However, as noted earlier, the effective use of this information to predict the system's performance on any given day is difficult if the system has not yet approached steady state, and seemingly paradoxical or otherwise confusing situations may be encountered by users. This would explain the tendency to revert to the "anchoring" adjustment strategy after a number of unsuccessful trials or after the user has identified an acceptable departure time that serves as an anchor for subsequent adjustment. Along the same line, it can be hypothesized that there is a clearer compensatory feature in (at least some) users' behavior, whereby the trade-off between travel time and schedule delay is explicitly considered, as this trade-off becomes more apparent and salient to users when they are supplied complete information. This hypothesis will be further explored in subsequent modeling work.

An essential difference between the plots in Figure 6 and those obtained in the first experiment concerns the evolution of the indifference band of tolerable schedule delay. It was claimed earlier, in explaining the overall dynamic performance of the system under the two informational situations, that providing users with more information generally raised their aspiration levels. The net result was a lower average schedule delay in each sector at steady state and a longer time period to reach this state. Figure 6 generally indicates a slower rate of increase of the indifference band, with more users rejecting any given schedule delay, than under limited information. This is further substantiated by examining the response, in each sector, to different levels of schedule delay (in 5-min increments), as explained hereafter.

The percentage of those users experiencing a given schedule delay on day $t-1$ who have changed their departure time on day t has been calculated for each sector on a weekly basis (each including 5 days; this aggregation is necessary in order to have a meaningful number of observations in each schedule delay category). Table 4 gives the principal trends by presenting a week-by-week comparison of these percentages for selected sectors and schedule delay values that typify the underlying patterns. In particular, in any given week and sector, when users are provided with more information, a higher fraction of those exposed to the same schedule delay choose to reject it and switch departure times on the next day, often for 2 or more weeks after all corresponding switching has subsided under limited information. This indicates that the indifference band is increasing at a slower rate, which reflects users' higher aspiration levels. Furthermore, it is noted that, during the system's evolution, users in the second experiment were exposed to schedule delays of the same magnitude as those encountered in the first. Therefore the higher switching frequencies and longer time to converge in the second case are not due to users experiencing higher schedule delays than in the first experiment but to users rejecting comparable outcomes, evidently in the hope of achieving ultimately better outcomes.

Intentions

User intentions are captured by the anticipated arrival time ($AAT_{i,t}$) provided by each participant i on day t, $i = 1, \ldots, 100$, $t = 1, \ldots, 30$, along with the departure time ($DT_{i,t}$). In the first experiment, it was found that users were much more willing to change actions ($DT_{i,t}$) before changing intentions, and that the time period between consecutive *AAT* changes decreased somewhat as the system evolved. In the second experiment, supplying users with complete information about the facility's performance led to a markedly greater willingness to change anticipated arrival time

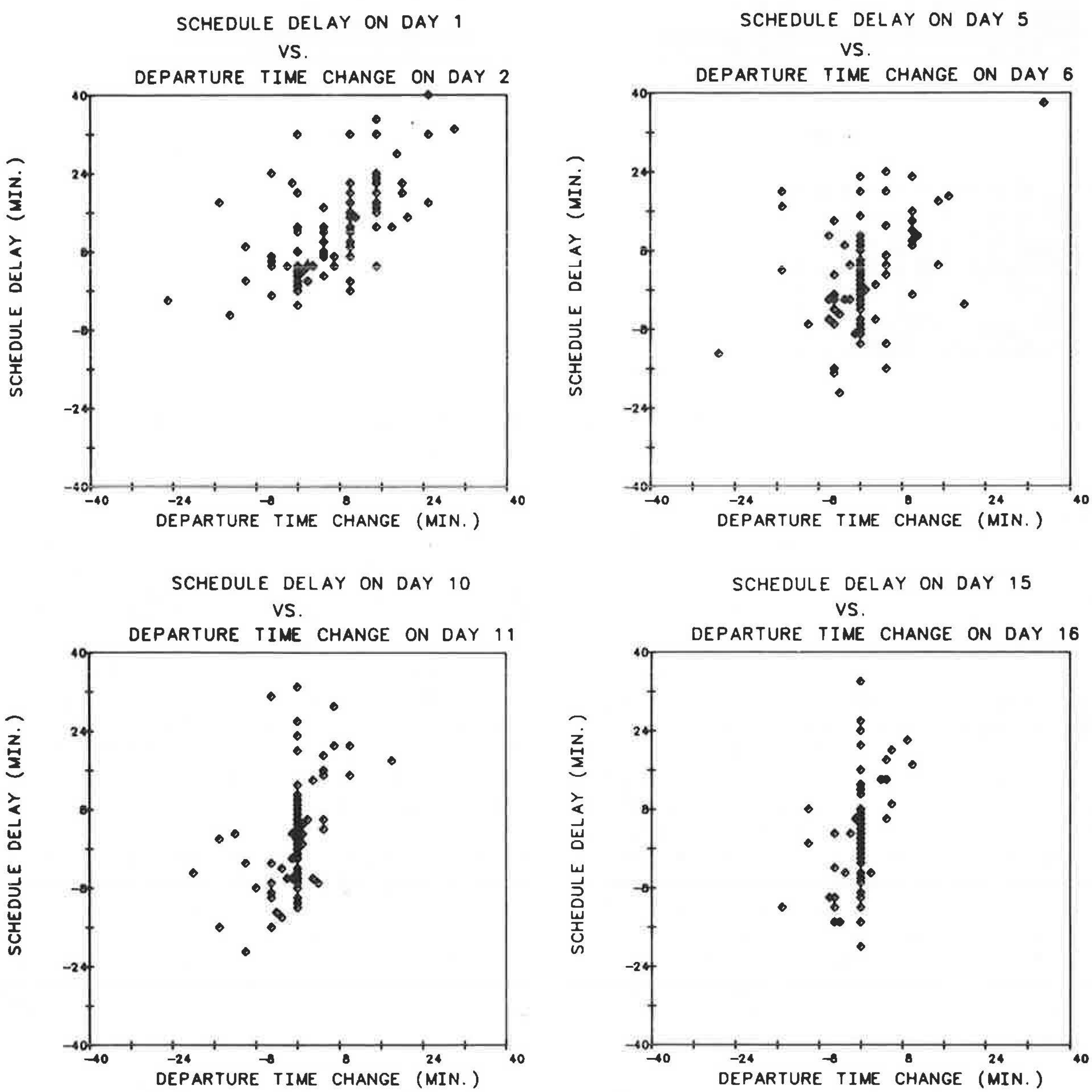


FIGURE 6 Scatter plots of departure time adjustment ($DT_{i,t} - DT_{i,t-1}$) versus schedule delay on previous day ($SD_{i,t-1}$) for selected days (t = 2, 6, 11, 16, 21, 26, and 30), Experiment 2.

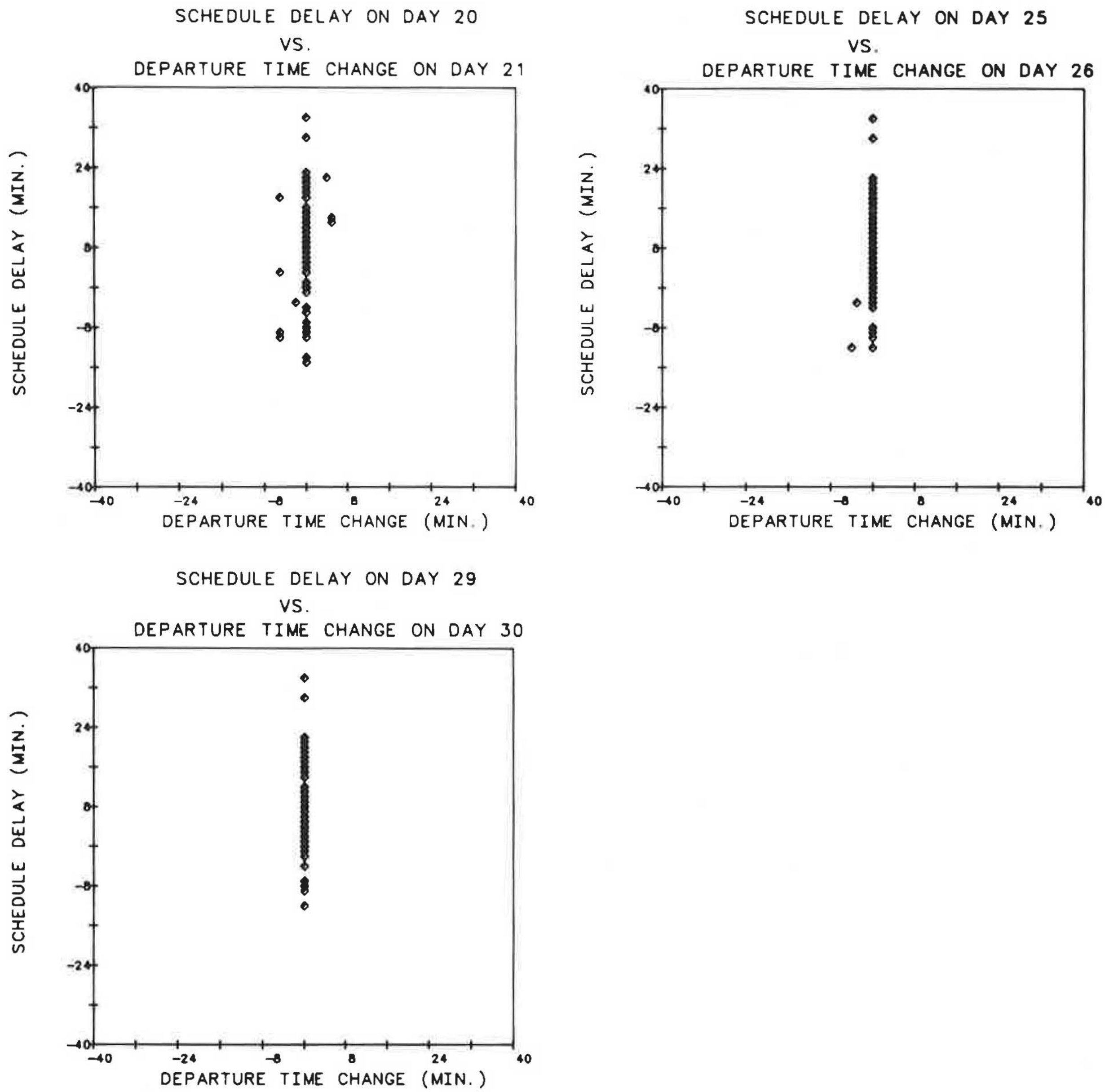


FIGURE 6 ***continued***

among users, without the initial resistance to changing intentions present in the first experiment. This is illustrated by the data in Table 5, which is a list of the percentage of users in each sector with at least n departure time changes, $n = 1, \ldots, 21$, for both experiments.

This greater propensity to revise anticipated arrival time is a plausible result of the availability of complete information on system performance. Under limited information, users perceived a greater level of uncertainty and were often not sure how to revise their *AAT*, especially at the beginning. However, as they progressively learned about the facility's performance, they were more willing to perform such a revision. In the first experiment, a clear decreasing pattern in the average time between consecutive *AAT* changes was present *(2)*. No such pattern is present in the second experiment.

The effect of *PAT* group on the frequency of *AAT* changes is essentially similar to its effect on departure time switching frequency. Group 1 users, with the earliest *PAT*, generally tend to experience less switching frequency than those in later *PAT* groups. Group 3 users still appear to exhibit the highest switching frequencies overall, though they are closely matched or surpassed by Group 2 users in some sectors. The significance of differences across these two groups cannot be ascertained on the basis of this exploratory analysis and will be addressed in formal statistical work, similar to that discussed elsewhere *(3–4)* for the first experiment.

Perceptions and Learning

Two principal aspects are addressed here: (*a*) how commuters use the information with which they are supplied in predicting their travel time and (*b*) the accuracy of their predictions as the system evolves. In the first experiment, travel time prediction models were calibrated at the individual level, which revealed that travel time on the previous day ($t - 1$) was the overwhelmingly dominant

TABLE 4 COMPARISON OF USER RESPONSE TO PREVIOUS DAY'S SCHEDULE DELAY: PERCENTAGE OF USERS EXPERIENCING GIVEN SCHEDULE DELAY WHO SWITCH DEPARTURE TIME ON FOLLOWING DAY, BY WEEK, UNDER BOTH EXPERIMENTS, FOR SELECTED SECTORS AND SCHEDULE DELAY VALUES

		Week					
Sector	Experiment	1	2	3	4	5	6
Schedule Delay of 11 to 15 min (early arrival)							
1	1	90.0	60.0	11.1	0		
	2	90.9	66.7	12.5	10.0	13.3	0
2	1	73.7	66.7	0	0		
	2	62.5	64.7	20.0	38.5	0	0
3	1	100.0	31.25	0	0		
	2	71.4	66.7	40.0	20.0	20.0	0
5	1	58.3	0	0	0		
	2	77.8	33.3	0	0	0	0
Schedule Delay of 6 to 10 min (early arrival)							
2	1	69.2	0	0	0		
	2	60.0	70.0	26.7	23.1	5.3	0
4	1	0	0	0	0		
	2	41.2	43.8	25.0	0	0	0
Schedule Delay of –1 to –5 min (late arrival)							
2	1	11.1	22.2	17.7	11.1		
	2	81.8	75.0	71.4	27.3	5.3	0
Schedule Delay of –6 to –10 min (late arrival)							
5	1	80.0	0	0	0		
	2	75.0	60.0	20.0	0	0	0

TABLE 5 FRACTION OF USERS IN EACH SECTOR WITH AT LEAST n ANTICIPATED ARRIVAL TIME CHANGES

No. of	Sector 1		Sector 2		Sector 3		Sector 4		Sector 5		All Sectors	
Changes	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 1	Exp. 2
1	75	90	75	90	80	100	30	90	35	90	59	92
2	50	85	60	90	25	100	5	90		85	28	90
3	20	85	30	90	10	90		65		70	12	80
4	15	75	10	85		90		65		65	5	76
5	15	70	5	80		85		60		50	4	69
6	10	65		75		85		55		45	2	65
7		55		75		85		45		35		59
8		55		75		80		30		35		55
9		50		65		75		30		35		51
10		50		65		60		15		25		43
11		50		45		55		15		15		36
12		45		45		40		10		15		31
13		30		45		40		10		10		27
14		25		35		35		5		5		21
15		15		15		25		5		5		13
16		5		15		25		5				10
17		5		10		20		5				8
18		5		5		15		5				6
19		5		5		15		5				6
20		5				10		5				4
21		5										1

Note: Exp. = experiment.

explanatory variable (anticipated travel time, defined later, is the dependent variable), with actual experienced travel time on day $t-2$ also being a significant variable statistically for some user groups, though its coefficient was an order of magnitude less than that of $TT_{i,t-1}$ (3). No elements in the time series were significant beyond $t-2$. However, that analysis also revealed a rather thorny empirical problem in the definition of predicted travel time. The use of anticipated travel time $ATT_{i,t} = AAT_{i,t} - DT_{i,t}$ as a proxy suffers from its reliance on two decision variables (*AAT* and *DT*) selected by the participant, often without explicit concern that their difference corresponds to travel time. Furthermore, some participants may not have been careful with their specified *AAT* because they knew that its value would have no bearing on the actual outcome. Therefore, the anticipated travel time cannot always be interpreted, strictly, as a predicted travel time. Nevertheless, it provides useful insight into a process that is probably one of the least understood and least researched in travel behavior.

Unlike the first experiment, providing users with complete information offers greatly expanded opportunities for learning and introduces yet another level of complexity in the process. Because users are exposed to more information on any given day, their ability to retain much of this information beyond the immediately preceding day (which is displayed to them when they select their departure time) is greatly diminished. Essentially, one of two principal quantities, or possibly both, can be expected to play a dominant role in determining $ATT_{i,t}$, namely (*a*) the actual travel time experienced on the previous day ($TT_{i,t-1}$) and (*b*) the supplied travel time, also on day $t-1$, corresponding to the departure time selected on day t. Naturally, if departure times on day t is not changed, the two quantities are identical.

Figure 7 shows the day-to-day evolution of the mean absolute value of the difference between the anticipated travel time ($ATT_{i,t}$) and these two quantities, respectively, for each sector. As expected, the two curves tend to coincide toward the end of the experimental

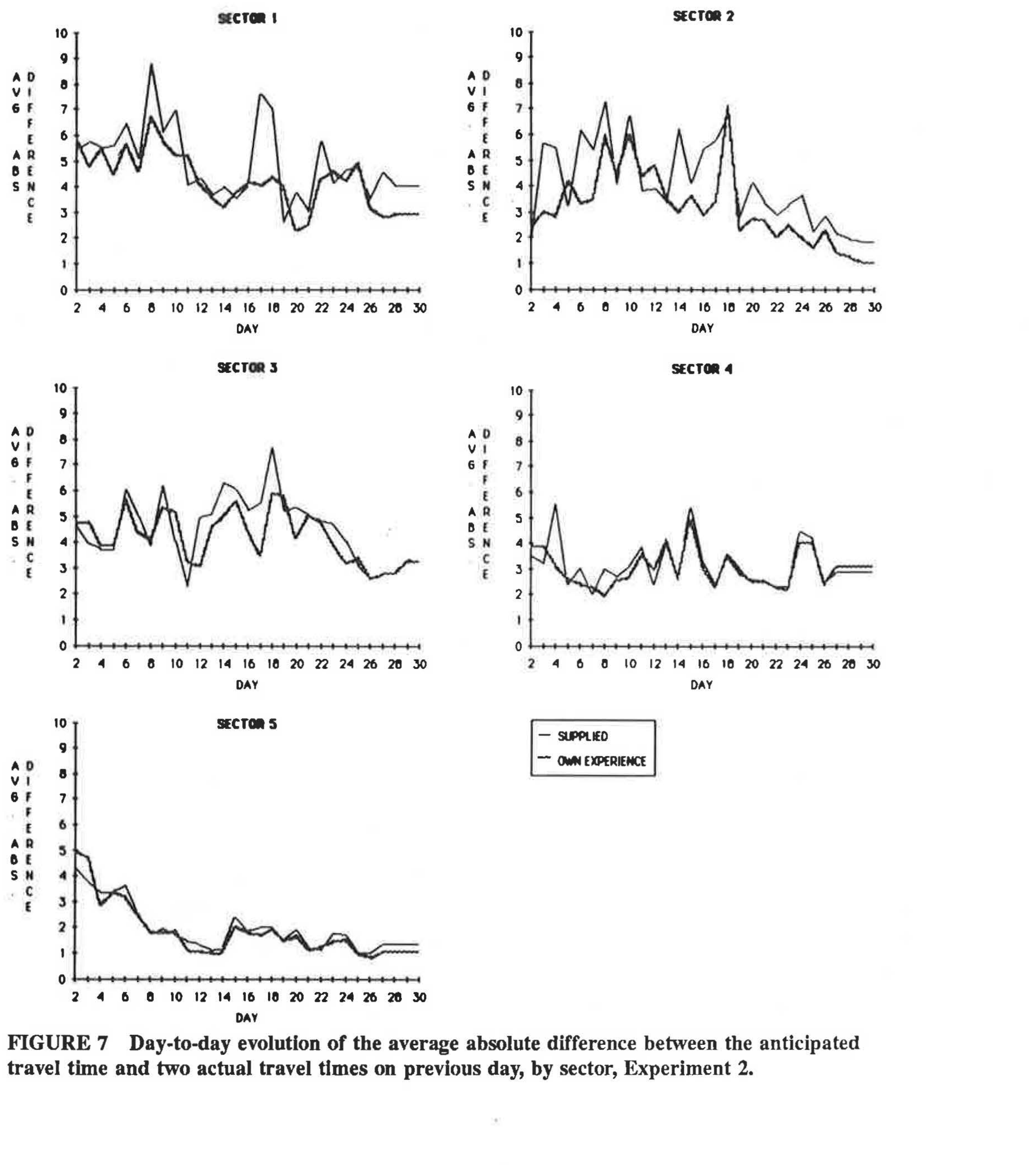


FIGURE 7 Day-to-day evolution of the average absolute difference between the anticipated travel time and two actual travel times on previous day, by sector, Experiment 2.

period, as steady state is approached and fewer people change departure time. This holds over most of the experiment in the closest sectors (4 and 5, as shown in Figure 7). Overall, it appears that the average difference is generally smaller relative to the actual experienced travel time than to the supplied travel time corresponding to the selected departure time, as defined previously. It is also clear that users are not simply taking one or the other quantity as the anticipated value for the current day but are subjecting this information to some level of processing. Furthermore, it can be expected that different strategies will be employed by different trip makers, with varying degrees of reliance on the supplied information. Further exploration of these questions will be pursued in more formal mathematical model development.

Finally, the quality of the users' predictions is examined. Figure 8 shows the evolution of the average (absolute value of the) difference between the anticipated and actual travel times on each given day (i.e., $| TT_{i,t} - ATT_{i,t} |$) for the second experiment. Note that this difference is also identical to $| SD_{i,t} - ASD_{i,t} |$, where $ASD_{i,t}$ is the anticipated schedule delay by user i on day t. In all cases, there is a noticeable decreasing pattern in the first few days of the experiment. A steady increasing pattern then appears in Sector 3 (Figure 5), which indicates that users' predictions were getting worse from one day to the next and thereby explains the intense departure time switching activity exhibited by this sector. Considerable fluctuation is seen in this sector, as well as in Sector 2 (Figure 5), even though the dynamic pattern for the latter differs by the occurrence of unexpected (by the users) peaks (e.g., days 7 and 17) that are followed by periods during which the difference generally decreases at a fairly steady rate. This pattern is also found in Sector 1 but with less extreme peaks. The closer sectors, 4 and 5, exhibit generally less extreme fluctuations, as expected, even though the distinct worsening and turbulence seen in the more distant sectors during the period ranging from day 15 to 18 are also reflected, though to a lesser extent, in these closer sectors.

Comparing the plots of Figure 8 with similar ones for the limited-information experiment, shown elsewhere *(2)*, is quite

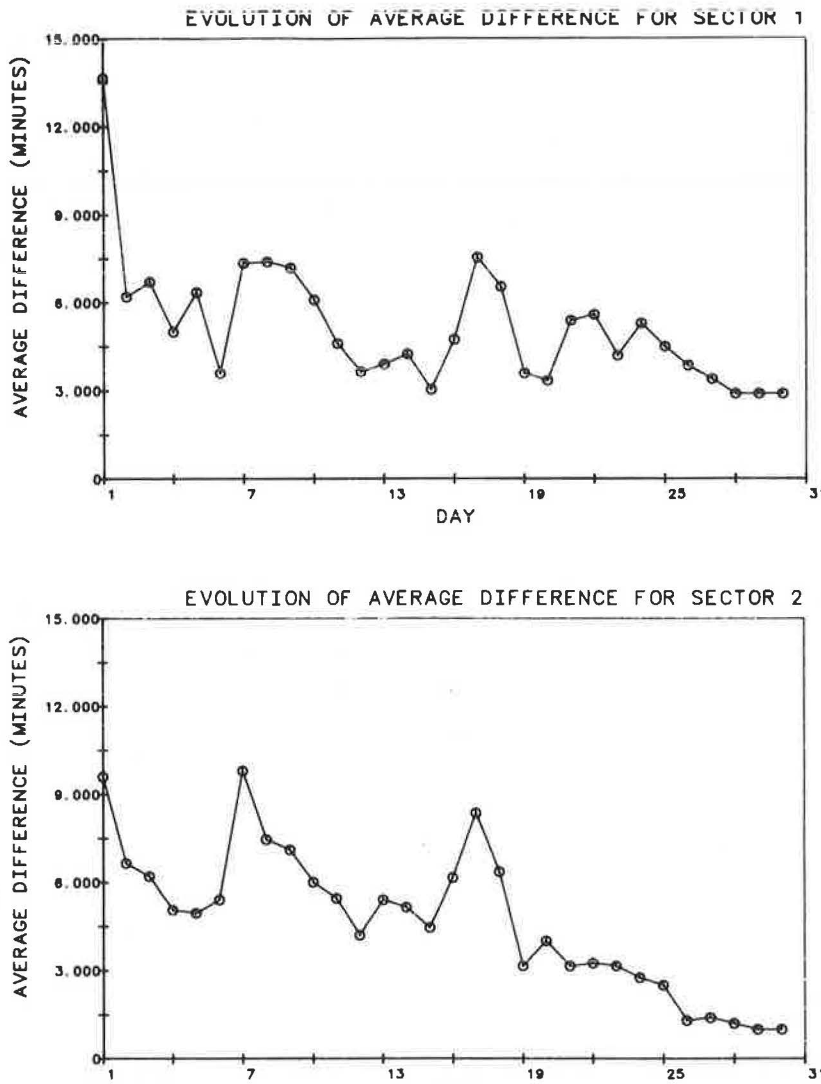
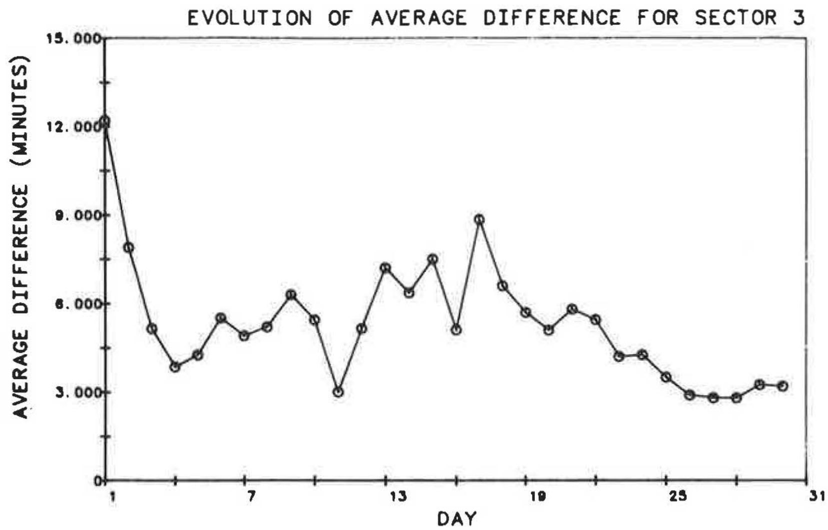
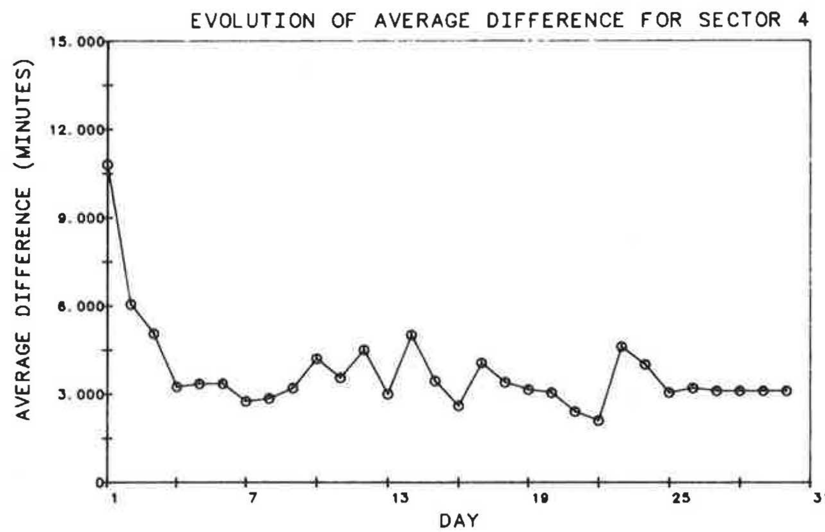


FIGURE 8 Day-by-day evolution of the average absolute difference between actual and anticipated travel time, Experiment 2.





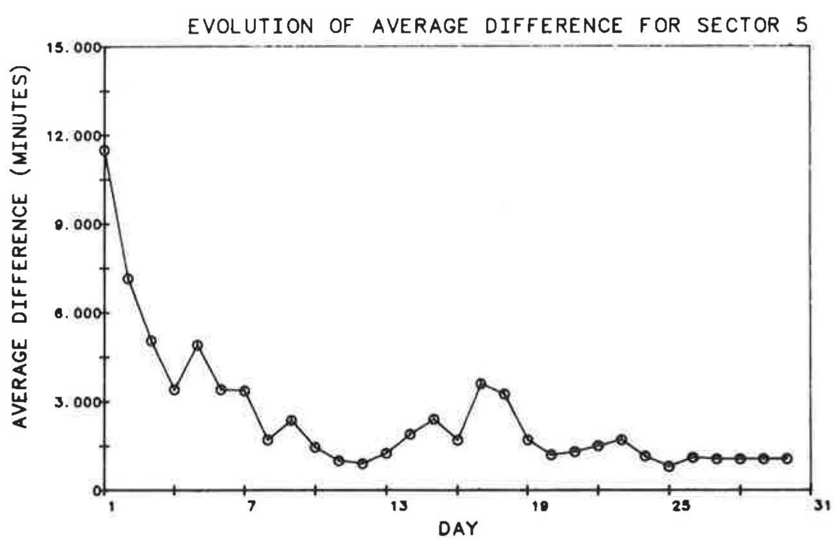


FIGURE 8 ***continued***

revealing and is consistent with the earlier interpretation of the effect of information on user behavior and the resulting performance of the system. In particular, providing users with more information did indeed improve their prediction of the system's performance, which is reflected by the consistently lower average differences observed for virtually all sectors in the second experiment. Furthermore, the dynamic pattern exhibits fewer erratic fluctuations under the complete-information situation. For instance, in the first experiment, a high value was typically followed by a low one, and vice versa, throughout most of the first 3 weeks, especially in the more distant sectors, and no detectable decreasing pattern emerged until the system closely approached steady state. This is not the case in the second experiment, in which clear decreasing patterns could be detected in all sectors over significant portions of the experiment (or, in Sector 3, increasing patterns resulting in user frustration, confusion, and switching). However, as mentioned earlier, the interactions taking place in this dynamic commuting system are quite complex, which results in the predictable jumps. Therefore, although providing users with more information has generally improved their ability to predict the system's performance, it has also raised their expectations, which, coupled with the inherent complexity of the system and the associated unpredictable shocks, has resulted in the increased frequency of switching and longer convergence time relative to the limited-information situation.

CONCLUSIONS

Comparison of the results of two experiments involving real commuters interacting in a simulated traffic system, under two distinct informational situations, has confirmed that the provision of additional information influences user behavior and the resulting overall performance of the system. The results were examined from the perspective of a behavioral framework proposed in previous work, in which users are viewed as boundedly rational seekers of an acceptable departure time, who behave as if they had a dynamically varying indifference band of tolerable schedule delay. Although the present paper is primarily exploratory in nature, important insights into the nature of the effect of availability of information on the dynamics of departure time decisions have been presented. These insights constitute the principal hypotheses that guide subsequent formal model specification, estimation, and testing.

Providing users with complete information on the previous day's performance of the system has apparently raised the aspiration levels of most of these users, as reflected in the slower increase of their indifference band. Although the additional information proved generally helpful in improving their performance prediction capability, the complex interactions in the traffic system preclude complete predictability. The juxtaposition of effects resulted in higher departure time (and anticipated arrival time) switching frequency levels and a longer convergence time to steady state than under limited information. However, the steady state ultimately reached proved superior, in terms of user costs, to the one attained under limited information.

Although quite insightful into important phenomena that have to date benefited from virtually no significant research, due, to a large extent, to the difficulties and the scale of obtaining appropriate observational data, the experimental procedure followed here involves obvious restrictions due to the simulated nature of the commuting corridor. This paper, however, further illustrates its usefulness in exploring the dynamics of user behavior in complex traffic systems and as a tool to support theory and model development that could ultimately be subjected to field verification.

Regarding the comparability of the test situations considered in the two experiments to real-world commuting systems, it can be noted that both are probably extreme. Commuters usually do not routinely have access to nor do they explicitly rely on information that is as comprehensive as that supplied in the second experiment. On the other hand, users might have access to more than just their own performance through word-of-mouth or media reports that they only passively receive. Therefore, real-world situations, although naturally exhibiting a certain degree of variation, tend to be somewhere between the two informational situations considered in the experiments. This aspect would undoubtedly benefit from further probing, as fine tuning generally follows extreme cases intended to provide useful bounds on the range of system behavior that can be expected. The results of these experiments also suggest potentially promising avenues for the control of commuting systems, as they begin to illustrate the potential role of information in improving overall system performance (reflected here through lower user costs at steady state). On the other hand, the evolution toward this improved state may be turbulent, as suggested by the longer convergence periods observed in the second experiment. In addition to the costs incurred in the transition, the length of this period could be excessive, and instabilities might prevail, possibly precluding the attainment of steady state. It would be desirable to understand how the convergence process can be controlled through provision of information. Experiments such as those described here provide a good starting point for developing this understanding.

ACKNOWLEDGMENTS

The authors are indebted to Robert Herman for many fruitful discussions on various aspects of the research effort involving the dynamics of user behavior in traffic systems. The authors are also grateful to Gang-Len Chang for his collaboration and tremendous help in conducting this second experiment, as well as his intellectual contribution to the evolving paradigm. Funding for the work presented in this paper and for continuing efforts in this area was provided by a National Science Foundation grant.

REFERENCES

1. H. S. Mahmassani, G.-L. Chang, and R. Herman. Individual Decisions and Collective Effects in a Simulated Traffic System. *Transportation Science* (under review).
2. 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.
3. G.-L. Chang. *Departure Time Dynamics in Urban Transportation Networks*. Ph.D. dissertation. University of Texas at Austin, 1985.
4. H. S. Mahmassani and G.-L. Chang. "Specification and Estimation of a Dynamic Departure Time Acceptability Mechanism." Presented at 65th Annual Meeting of the Transportation Research Board, Washington, D.C., 1986.
5. H. Simon. A Behavioral Model of Rational Choice. *Quarterly Journal of Economics*, Vol. 69, 1955, pp. 99–118.
6. 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. 107–121.
7. H. S. Mahmassani and G.-L. Chang. Experiments with Departure Time

Choice Dynamics of Urban Commuters. *Transportation Research B* (in press).

8. J. Horowitz. The Stability of Stochastic Equilibrium in a Two-Link Transportation Network. *Transportation Research B*, Vol. 188, No. 1, 1984, pp. 13–28.
9. H. S. Mahmassani and G.-L. Chang. On Boundedly-Rational User Equilibrium in Transportation Systems. *Transportation Science* (under review).

DISCUSSION

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In this and an earlier paper *(1)*, Mahmassani et al. have described two experiments in which the consequences of departure time choices of real commuters are evaluated using a special purpose simulation model. The results of their experiments provide valuable insight into a field of research that, until now, has not been extensively studied. This discussion of their work is intended as an addition to their studies not as a critique.

A central position in their model is given to the notion of an "indifference band" of tolerable schedule delay, where schedule delay is defined as the difference between preferred arrival time and actual arrival time. It is assumed that a user considers a particular departure time acceptable (and, as a consequence, will not change departure time the following day) if the resulting schedule delay is within that user's indifference band. The indifference band is expected to be dependent on each individual's preference, observable characteristics, and related environmental factors. Furthermore, the indifference band can vary dynamically with each commuter's perceived system performance variability. This latter proposition will be discussed later in more detail.

MEASUREMENT OF INDIFFERENCE BAND

The authors partition the indifference band into two components, an early side and a late side *(1)*. The early side of the indifference band is defined as the tolerated arrival times before the preferred arrival time, and the late side as the tolerated arrival times after this preferred arrival time. They propose to build a formal mathematical model to estimate these two components, apparently assuming that these cannot be observed or measured directly. That is true insofar as measurement with a yardstick or stopwatch is concerned; however, there exist psychometric methods to measure such an indifference band. One of these has been used in our own study on preferences for departure times *(2, 3)*. The method can be used to measure arrival times as well. In short, the method is as follows:

1. In addition to being asked for preferred arrival time (which Mahmassani et al. did ask), subjects are requested to estimate the times before and after this preferred arrival time that they consider to be (almost) as acceptable as their preferred time. The period between these two times is considered to constitute the indifference band.

2. Furthermore, subjects are asked to give estimates of the earliest and latest time at which they are willing to arrive.

On the basis of these four estimates a trapezoidal distribution can be fitted (Figure 9) with the additional assumption of either an equal total area for each subject or an equal height at the most preferred times. The choice of restriction would depend on the problem under consideration.

The results of our study support some of the assumptions and findings of Mahmassani et al. For example, the indifference band

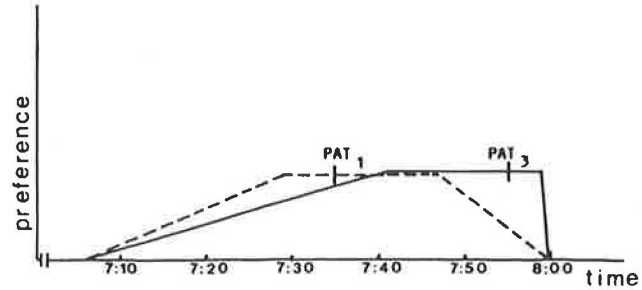

FIGURE 9 Time preference distributions for members of Group 1 and Group 3 (PAT_1 = preferred arrival time of a Group 1 subject and PAT_3 = preferred arrival time of a Group 3 subject).

correlated significantly with age *(5)*, and a significant interaction was found among journey motive, gender of the subject, and direction of the journey (from home or return home). For the journey to work an average was found of 54 min for the total acceptable period and of 18 min for the indifference band. Mahmassani and Chang *(1)* reported that no user experiencing lateness of up to 5 min or earliness of up to 10 min (relative to his respective preferred arrival time) decided to adjust departure time on the following day, which indicates that these deviations fell within the indifference band. The width of the indifference band would, then, be at least 15 min, a value remarkably close to the 18 min found in our study.

Mahmassani et al. divided the commuters in their experiments into three groups, according to their preferred arrival times: Group 1 preferred to arrive between 7:30 a.m. and 7:40 a.m., Group 2 between 7:40 a.m. and 7:50 a.m., and Group 3 between 7:50 a.m. and 8:00 a.m. To illustrate the method two hypothetical arrival time preference distributions are depicted in Figure 9, one for a Group 1 member and the other for a Group 3 member. As the preferred arrival times (*PAT*), the midpoints of Mahmassani's group intervals, are chosen, the widths of the indifference bands and total acceptable periods are set to the average values found in our study. Furthermore, earliest and latest times are assumed to be equal (in the experiment work starting time was stressed to be 8:00 a.m., sharp).

The advantage of this psychometric measurement method is that it takes account of arrival times that are preferred less than those within the indifference band but that are still acceptable to people. Moreover, the method enables the researcher to quantify time preferences as a more continuous variable (namely, as the height of the preference distribution at a specific arrival time) instead of a binary one (as Mahmassani et al. essentially do).

UNDERLYING BEHAVIORAL PROCESSES

As Mahmassani and Tong have already stated, in the experiments at least two behavioral processes take place. First, subjects have to learn the travel times in the particular system, a rather difficult task because travel times will vary as long as steady state is not reached. The second process, according to Mahmassani and Tong, is the revision of the aspiration level (i.e., the indifference band). In our opinion, it is not the indifference band that is revised. The seemingly dynamic nature of the indifference band is a consequence of the definition Mahmassani and Tong use: that the indifference band is the tolerated schedule delay (i.e., the tolerated difference between preferred arrival time and actual arrival time). We would suggest that the second task of the subject is minimizing travel time while maximizing preference for an arrival time (defined as the height of the time preference distribution at that particular time), in essence a two-dimensional task. Individual differences can exist in the weighing of dimensions and the width of the time preference distributions. This two-dimensional decision process can very well result in an accepted arrival time outside the indifference band but within the total acceptable interval, as long as this arrival time occurs together with a preferred travel time. An indication that travel times are important indeed, is the finding reported by Mahmassani and Tong that in the second experiment travel times for most sectors were much lower than in the first experiment. The decision process is further complicated because the travel times are not known by the subject and are, furthermore, varying until steady state is reached. This results in a difficult task not only for the subject but also for the researcher. To get more insight about the decision process it would be interesting to carry out an experiment in which the subjects received bogus feedback on their travel times. In this way the experimenters could manipulate the length of the travel times and schedule delays. The experiment would, admittedly, lose some generalizability; the increased potential for insight, however, could very well compensate for this.

A second, less strong reason for our doubts about a dynamic indifference band is that in our study the test-retest correlations for the indifference band (with half a year between tests) appeared to be reasonable to rather high: .52 for the width of the indifference band and .98 for the two times that form the bounds of the indifference band.

PEAK-HOUR TRAFFIC: A SOCIAL DILEMMA

Peak-hour traffic can be described as a specific type of social dilemma, namely a chicken dilemma *(5)*. In a chicken dilemma, a person can choose one of two strategies: either cooperate (C) or defect (D). Unlike the situation in a prisoner's dilemma game, there is no dominating strategy in the chicken dilemma (i.e., there is no particular behavior that enhances personal gains in all circumstances). A choice for defecting only yields the highest payoff if more than a specific number of other persons choose to cooperate. To illustrate the applicability of the chicken dilemma paradigm, we will use a very simplified version of the problem at hand.

Consider the choice of persons, all living in the same sector, between two specific departure times. If everyone chooses the late departure time, the result will be congestion. If some persons decide to leave early they will benefit (by shorter travel times), and the others will suffer less (by some reduction of the congestion). However, if all persons decide to leave early the result is again congestion. Whether the choice of a particular subject for a specific departure time (early or late) should be considered as cooperative or defective depends on the behavior of the other participants and on the payoff structure. When most subjects prefer to leave late, leaving early cannot be regarded as purely cooperative: the subject leaving early also profits from this choice (by having a shorter travel time). Conversely, if all people leave early, a choice for a late departure time cannot be considered strictly defective: although the person leaving late profits from this choice, other subjects also benefit (by a reduction of congestion). We will, therefore, refer to leaving early as Strategy A and to leaving late as Strategy B. Furthermore, because in the present case the choice of a particular departure time cannot be consistently denoted as cooperative or defective, we must relax one of the assumptions of the chicken dilemma, namely that the payoff given that all persons cooperate is higher than the payoff given that all persons defect.

The payoff structure of this particular chicken dilemma is rather complicated because it is clear that several factors interact. For example, if no one chooses to leave early, the costs could be longer travel times and the chance of being late, but [if leaving early is indeed preferred less, as the findings reported *(1)* suggest] all would benefit by not having to leave early. On the other hand, if all participants choose to leave early, all encounter the costs of leaving early and of longer travel times, but the chance of being late would be much less. An example of such a payoff structure is shown in Figure 10 with the costs of travel time, leaving early, and the chance of being late rather arbitrarily set at a ratio of 3:2:1.

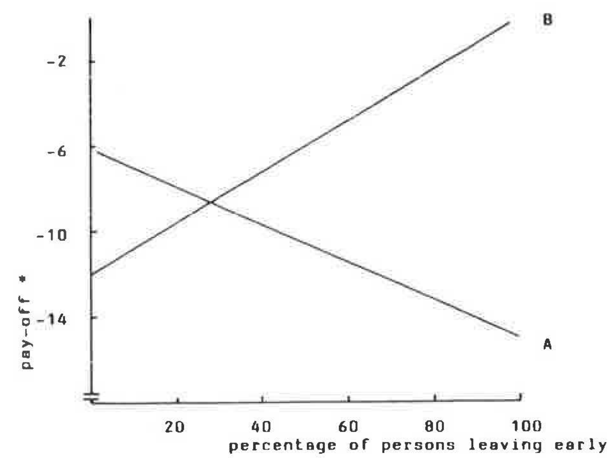

FIGURE 10 Payoff structure of Strategies A and B, expressed in arbitrary units.

If the payoff structure is correctly specified, the point where the lines representing the two strategies intersect would be expected to give the percentage of persons leaving early in steady state.

As was mentioned previously, this is a very simplified version of the problem Mahmassani et al. tackle. In the experiment (as in reality) people could choose between more than two departure times. Existing models for the chicken dilemma should, therefore, be extended to more than two choices.

It might be useful to apply social dilemma models to the analysis of Mahmassani's task. One of the things that become clear is that more insight is needed about the payoff structure: What is perceived as benefit or cost? Are there individual differences in these perceptions, and how are the factors that determine the payoff weighed?

From the social dilemma literature several factors are known to affect choice behavior *(5)*. One factor of particular interest for the present case is the expectation a subject has about other people's behavior. Expectations are important because the question whether

Strategy A or B is advantageous depends, in the chicken dilemma's payoff structure, on other people's choices. Information concerning collective choice behavior may influence participants' expectations of others' choice behavior and, in turn, these expectations may influence their actual behavior. Thus, in terms of the present problem, if people are informed that numerous others are leaving early, the best strategy is to leave late. On the other hand, if people are informed that very few are leaving early, the best strategy is to leave early (see the payoff structure in Figure 10).

In Mahmassani's second experiment, subjects were provided with information about the performance of the system on the previous day, specifically with arrival times corresponding to an array of posible departure times. This information would enable a subject to select the departure time that would result, hypothetically, in the shortest travel time and the most preferred arrival time (i.e., within the indifference band). The results of the second experiment provide some evidence for this point of view: for most sectors travel times were shorter in the second experiment, as were schedule delays for Sectors 1 and 2. It could be argued that the feedback provided to the subjects may also have had some confusing effects. Subjects may have been tempted to choose a departure time associated with the shortest travel time on the previous day, underestimating the effect of other participants using the same strategy. At least in the initial stages of the experiment, this may have resulted in delays. It probably took subjects some time to resist these seemingly advantageous choices, as a result of which a longer convergence time was obtained. One of the possible ways to investigate this process is to examine the relationship between choice of departure time and travel times on the previous day that were presented as information (i.e., not just own travel time on the previous day as Mahmassani et al. analyzed), in combination with preferred arrival time.

Mahmassani et al. express concern over the longer period it took to reach steady state. It could be that information directed at a better assessment of other people's behavior (enabling subjects to have more realistic expectations of other people's behavior) would shorten the convergence period. Supplying information on the number of travelers at particular times (adjusted for distance differences between sectors) could be considered.

We would like to conclude with the observation that Mahmassani et al. have presented a very interesting research method, which is undoubtedly a valuable contribution to this field of study. In our view, further research in this area might benefit from the development of appropriate extensions of the chicken dilemma and from the use of psychometric methods for the assessment of individual departure and arrival time preferences.

REFERENCES

1. H. M. 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.
2. C. van Knippenberg, J. Michon, and M. Hoekert. "Bus Use in Rural Areas: People's Time Preferences." *Proc., International Conference on Transport's Role in Social Well-Being*, Noordwijk, The Netherlands, 1983, pp. 180–191.
3. C. van Knippenberg and M. Clarke. Taking Account of When Passengers Want to Travel. *Traffic Engineering and Control*, Vol. 25, 1984, pp. 602–605.
4. C. van Knippenberg and J. Splinter. *De relatie tussen openbaar vervoer en mobiliteit in keline kernen* (in Dutch). Research Report VK 83–03. Traffic Research Centre of the University of Groningen, The Netherlands, 1983, Appendix B.
5. W. B. G. Liebrand, H. A. M. Wilke, R. Vogel, and F. J. M. Wolters. Value Orientation and Conformity: A Study Using Three Types of Social Dilemma Games. *Journal of Conflict Resolution*, Vol. 30, 1986, pp. 77–97.

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On-Board Bus Surveys: No Questions Asked

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In this paper is described an on-board bus survey procedure that allows collection of data about the pattern of use of the bus system within each bus route and limited data on transfer patterns. The procedure is a simple one that involves the passenger accepting a colored, imprinted card when boarding the bus and returning this card on alighting from the bus. The survey therefore obviates the need for passengers to respond to questions, which is of particular value for bus systems the patrons of which may speak a variety of different languages and may be unwilling or unable to respond to a survey in English. The analysis procedures for the survey results are simple and can be executed rapidly, which allows results to be obtained within a matter of days or weeks of survey execution, compared with the months more normally encountered for standard on-board surveys. The survey procedure has also been found to generate a high response rate. In an urban area that had previously shown poor on-board survey responses even with a multilingual instrument, a response rate of between 85 and 98 percent was achieved on a route-by-route basis.

There appears to be a growing interest in conducting bus-rider surveys, particularly on-board bus surveys, as various bus operators find themselves faced with the need to redesign services in an effort to cut costs without too great an impact on transit-dependent patrons. Bus-rider surveys can take a variety of forms *(1-3)* including on and off counts at specific points, farebox sample surveys, self-administered survey forms, on-board interviews, and simple ride checks. The amount of information generally possessed by most bus operators is more variable still than the methods for conducting ridership surveys. The extremes are defined by those operators that conduct on-going monitoring of ridership levels through ride checks and counts, supplemented frequently by interview surveys of bus riders, and those operators that have no on-going information-collection activity apart from farebox counts, from which they derive estimates of ridership for annual reports.

The attitudes of bus operators to ridership information are also varied and depend on their view of the goals and objectives of bus service. Increasingly, the attitudes of operators are changing to a recognition that bus operations provide a service in a competitive market. This change in attitude is bringing with it acceptance that data are needed on the positioning of the product called "transit service" in the market of transportation services. Data are also required to identify the users of transit service and how these users make use of the service.

Ride checks *(2)*, perhaps the commonest form of frequent data collection for bus operations, do not provide adequate information on how the user is consuming the product of transit service. Ride checks provide information on boardings and alightings by stop and the total loads on a bus route at various points along the route, thereby allowing definition of the maximum load point. However, ride checks do not provide information on the travel pattern of individual users of the bus system. However, there is a method for developing route origin-destination (O-D) information from on-off counts, with some major limitations *(4)*.

In general, to determine the patterns of use of the system requires some method for tracking the behavior of the individual user. Many European transit systems have a built-in mechanism for obtaining such data, provided by a ticketing system that records both the boarding and alighting points, to allow a staged fare to be charged. However, in systems with flat fares and no tickets, such as those operating in the United States, passengers do not use any fare mechanism that provides a means of tracking their travel behavior. As a result, U.S. operators, more than their European counterparts, must resort to some type of passenger survey to determine how the system is used.

Passenger surveys are, however, posing more and more difficulty. Apart from the often-encountered resistance to surveys of the bus-riding public, there is a growing language problem that makes it difficult indeed to devise any type of self-administered or interview instrument that can provide data on a representative sample of bus riders.

The specific situation that gave rise to the development of the survey described in the balance of this paper involved language problems that were expected to cut severely into the representativeness of any survey that employed any form of traditional self-administered or interview instrument. In the survey location—Dade County (Miami), Florida—the following conditions existed:

- A bilingual survey conducted in 1980 had achieved only a 20 percent response rate from a self-administered survey form *(5)*.
- A second bilingual survey in 1982, administered simultaneously in five other urban areas in the same state, achieved a response rate of 23 percent compared with an average of 86 percent in the other urban areas *(6)*.
- Data were needed on passenger travel patterns to allow a major redesign of the system to be accomplished without substantial loss of service to existing patrons.
- An ordinance had been passed by referendum since the 1980 survey declaring English the official language of the county and prohibiting use of county funds to translate or print material in any language other than English.

The last of these conditions meant that any traditional survey undertaken could be presented only in English. The bus ridership to be surveyed included Spanish speakers and Haitians, as well as others with native languages other than English, most of whom could be expected to be unable or unwilling to read or respond to a survey conducted only in English. Clearly, representativeness could not be expected from any survey that was based on questioning bus riders. Furthermore, it is apparent that bus riders in Dade County are unwilling to respond to on-board surveys, even when multiple languages are used.

After much effort was spent in considering the actual data needs, it was determined that by far the most important elements of data required are the origin and destination bus stops of bus riders and some information on the use of transfers within the bus

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system. Although data on the socioeconomic status of bus riders might be useful, socioeconomic status is not of utmost importance to the redesign of the system. Similarly, data on trip purpose, captivity to transit, actual origins and destinations, and modes of access and egress would all be useful to provide a more complete picture of bus use. However, none of these items was considered to be unequivocally essential for planning and initiating changes in bus routes, frequency of service, and service coverage. All of these desirable but nonessential data items require participation in a survey by the bus riders. In the situation defined here, the expected representativeness of a traditional survey procedure must be considered quite poor. Therefore a survey method was developed that would provide the essential information without involving the active response of bus riders in a question-and-answer survey.

The specific purposes to be served by the data were to provide sufficient information about existing bus users to allow changes to be made in bus routes that would minimize impacts on existing riders. At the same time, it was desired to identify potential changes in bus routes that would improve service or reduce operating budgets without signifiant loss of patronage. The bus system redesign, for which the survey was designed, was a wholesale restructuring of the system to reduce the operating costs significantly while retaining essential services and supporting the recently opened Metrorail system so as to increase rail ridership.

Ride-check data and farebox-based data were considered insufficient for this task. Such data can identify the volumes of boarding and alighting passengers on a route, and at specific bus stops, and can determine the location of the maximum load point, but they do not provide information on how far passengers ride nor on whether or not there are points on the bus route where the bus empties and then commences to fill with a new group of passengers. These are the types of information that it was believed would be helpful in determining how to restructure routes *(4)*. In addition, information was desired that would indicate whether early morning, late night, or weekend service could be curtailed, operated with short turnbacks, or otherwise reduced to save operating costs while losing a minimal number of passengers and amount of revenue.

SURVEY MECHANISM

Ideally, it would desirable to know the bus stop of boarding and the bus stop of alighting for each bus rider. In Dade County, as in many other large cities in the United States, there may be as many as 100 bus stops along a given bus route. Building 100 by 100 matrices for every bus line in the system would provide more detailed information than would ever be likely to be used and would place excessive demands on data processing and storage. It was decided, instead, to segment each bus route into as many as 10 segments and collect information on the segment of boarding and the segment of alighting of each passenger. Also, methods were considered for tracking information on transferring passengers. The ideal would be to know the bus stop for boarding of a transferring passenger and the stop of alighting. As is discussed later in this paper, this did not prove to be possible, although several different methods were attempted in the pilot survey—none with any remote success.

The survey mechanism used colors to identify each route segment. By assigning a different color to each segment of a bus route, color codes could be used to record when a passenger boarded the bus and when the same passenger alighted from the bus. The same sequence of colors was used for each bus route, although the number of segments on any route varied with the length of the route. To simplify execution of the survey, the segments were defined by the timing points used in building schedules for the bus system. These timing points are well known to the bus drivers, are used in all driver schedules, and are generally associated with transfer bus stops. They provide a useful and ready means of identifying route segments. Also, surveyors on the bus can obtain assistance from the driver in identifying the bus stop immediately preceding the timing point or at the street intersection that defines the timing point.

Survey Instrument

The first part of the survey instrument was designed as a small card, the same size and weight as a standard business card. These cards were imprinted with the bus system logo, to show the association of the survey with the bus operator, and with the route number of each bus route. Two additional numbers, described subsequently, were also printed on the cards. A typical card is shown in Figure 1. Cards were produced for each bus route in each of the colors required to identify all of the segments on the route. Because of limitations in the available card stock and constraints on differentiability of colors, the following color sequence was used on all bus routes: red, grey, yellow, blue, white, green, pink, tan, orange, and gold. If a bus route had only four timing points, defining three segments, the colors allocated to that route were red, grey, and yellow. If a bus route had six timing points, the five segments were coded red, grey, yellow, blue, and white. The same logic was applied to all routes, with the color furthest from red defined by the number of segments.

The second part of the survey instrument was a set of return boxes. These were made out of the boxes used to package business cards stuck to a strip of stiff cardboard (Figure 2). Each of the boxes in the strip was color coded, in the same sequence as the cards. In addition, black cards were cut, slightly smaller than the cross section of the return boxes, to be used as dividers between bus trips.

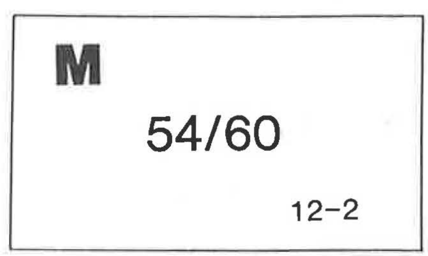

FIGURE 1 Example of the survey instrument.

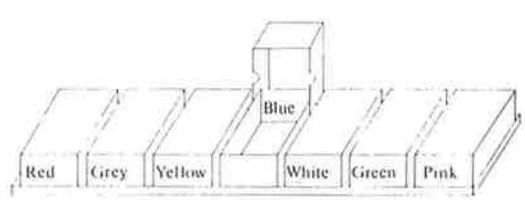

FIGURE 2 Return boxes

Survey Procedure

The survey procedure consisted of handing a colored card to each boarding passenger as the bus rider boarded the bus. The color of the card corresponded to the color coded to the segment of the bus route where the passenger boarded. On alighting, the passenger was asked to return the card, and the card was placed in the return box that corresponded in color to the segment of the bus route on which the passenger alighted. Thus, if a passenger boarded in the red segment of the bus route, he received a red card. If that same passenger alighted in the blue segment, the card was placed in the blue return box. Similarly, a passenger boarding in red and alighting in yellow would have his card placed in the yellow box. Thus, by counting the number of red cards in each return box, it would be possible to deduce the number of passengers that boarded the bus in the red segment and got off in each of the segments of the bus route.

In addition to the survey cards, surveyors collected transfers from the driver at each bus stop and placed these in the return box for the current segment of the bus route. This allowed determination of the number of passengers boarding in a segment who had transferred from another bus. Because the bus route number of the issuing route is recorded on the transfer, the number of transferring passengers by originating bus route was also obtained.

The survey procedure requires passengers to accept the colored card, hold it during the bus ride, and return it when they alight. To effect this, two surveyors rode most buses, one stationed immediately behind the farebox and one near the center exit door. The surveyor at the front of the bus handed out a card to each boarding passenger and also collected cards from those passengers (quite a large proportion in Dade County) who exited by the front door. It is possible for one surveyor to do these two things because the design of U.S. buses is such that passengers cannot both board and alight through the front door at the same time. The surveyor at the center exit has the task of collecting cards from all passengers leaving by that exit door. This procedures does not require any significant communication between surveyor and passenger, beyond the request for the passenger to take a card. This can be translated into several languages, if need be, but it was generally found in practice that there was little time to do more than ask passengers, in English, to take the card. A three-panel pictograph (Figure 3) displayed strategically in the bus communicated the requirement to take a card, hold it, and return it on alighting. This obviated the need to translate instructions into various languages.

Obtaining More Information on Transfer Passengers

As noted, it was desired to obtain specific information about transfer passengers. Several methods for doing this were considered. Of those considered, three were designated for testing in a pilot survey:

FIGURE 3 Pictograph used to instruct passengers.

- Stapling the colored card to the transfer and handing the two back to the passenger for retrieval when the passenger gets off,
- Marking the colored card with a "T" before handing it to the transfer passenger, and
- Punching a hole in the colored card before handing to the transfer passenger.

None of these methods was found to be workable because there is simply insufficient time to undertake these activities while handing out cards to boarding passengers. Also, it was impossible to watch which passengers used transfers and which did not while also handing out cards to all boarding passengers. Therefore it was decided that the only information to be collected from transfer passengers would be the boarding segment and the information already encoded on the transfer. To facilitate this procedure, bus drivers were asked to hand all transfers to the surveyor at the front of the bus after leaving each bus stop. Transfers were placed in the return box for the current segment color. Because the Dade County bus system does not use the transfers for any further purpose after they are handed to the driver and checked, this was a feasible method. In application to other systems, different procedures may be desirable for transfers, depending on local procedures for transferring passengers and information desired on transferring passengers.

Survey Sample and Execution

The sample was defined by selecting bus runs from each bus route in the system. The Dade County bus system has few lines that are operated interlined, and most of those are designated as dual routes for operation and analysis purposes (e.g., route 54/60). This makes sampling bus runs an easy method of administering the survey because a survey team placed on a selected bus will usually ride a single route for the entire time the bus is in service *(1)*. Bus runs for each route are assigned a unique number, beginning with 1. This bus run number was the second number printed on the survey cards. Thus bus runs are designated on "rotaries," the route operating schedules, and on driver "cards," the individual pieces of work assigned to each driver. Thus both the surveyors and the drivers knew the run number of the current operation. As a check that they were boarding the sampled bus, surveyors were instructed to check the run number with the driver.

The sample size was defined more for political reasons than on the basis of accuracy of the data. Dade County staff desired that a minimum 40 percent sample, covering bus operations for a weekday from start to end of operations and each Saturday and Sunday for the same period, be obtained. To a large extent, this sample size was set with the idea of being able to claim that a large number of riders had been included in the survey.

The sample was comprised of complete bus runs from each bus route. In many instances, this meant that the survey commenced at the bus garage, before the bus went into service. In such cases, the bus often commences service at the timing point nearest the garage, or at some other intermediate point, rather than at one of the end points of the bus route. At other times, survey teams boarded a bus in service, coincident with an operator change and, therefore, a run number change on an in-service bus. Because of the nature of both of these starting locations for a sample run, it was often the case that the survey would commence at some point in the middle of the route, rather than at the ends of the route as defined by the route map and the published schedule.

A team of two surveyors boarded a sampled bus. If a team was the one designated to commence the survey on that bus run, they boarded with survey materials for the entire run. These materials included signs to put up on the bus (requesting passenger assistance with the survey and showing what was expected of passengers) and the survey supplies. Each bus run consists of a number of one-way trips. These trips were numbered from 1 by the survey management for each sampled bus run. The number of trips per run is a function primarily of the length of the bus route, and ranged from 2 to 25 trips. The trip number constituted the third number printed on each survey card, to provide a check on the correct return of cards. To recap, the colored survey cards were imprinted with the bus system logo, the route number, the run number, and the trip number.

The survey materials for each bus run consisted of

- A "tailored" trip box for each trip on the sampled run;
- A supply of black divider cards equal to the number of trips multiplied by the number of trip segments;
- A supply of spare, blank red cards;
- The tray of return boxes; and
- Clipboards and color-coded maps of the bus route

The tailored trip boxes included one card box for each trip that the bus was scheduled to make on a sampled run and contained 60 cards banded together for each color of the route. The tailoring consisted of ordering the colors to correspond to the order in which the segments would be met on each trip and removing any colors that would not be needed on a trip. For example, the first trip, on a route with seven colors, might begin in blue and proceed to pink, so that only the colors blue, white, green, and pink in that order would be in the trip box for trip one. The cards in that trip box would be imprinted with the route number, the run number, and Trip 1. Trip 2 might then proceed from pink back to red, and all colors would appear in that trip box, but ordered from pink to red. On the third trip, the bus might make a short turn at the end of the white segment, so the colored cards would be ordered red to white. This system, although time-consuming to set up, was found to be essential to minimizing surveyor confusion when buses made short turns or began in midroute. Also, it ensured that the trip colors were always handed out in the correct order.

The black divider cards were provided to be placed in the return boxes at the end of each trip. This was necessary to be able to record the data on a trip-by-trip basis for analysis. Also, because passengers do not use the bus the same way that the schedule of the bus is designed, it is not sufficient to depend on the trip numbers to identify the trip from which the cards are received. On a number of bus routes, it was found that passengers stayed on the bus over the turn-around at the end of the line and then got off at some point further along the line, past the place that the passenger boarded. This was particularly the case where the bus had no layover at one end of the trip, or a minimal layover, and where the frequency of service was low.

The color coding was designed so that any route that began or ended in the Miami central business district (CBD) was coded red in the CBD. On routes that did not have an end in the CBD, a rule of coding colors from east to west and south to north was applied to maintain consistency. Because of the high concentration of routes in the CBD, the CBD-red rule meant that there were times when the bus would fill up in the red segment, and surveyors could run out of red cards. It was not reasonable to tailor the number of cards by color or by trip. For the survey in Dade County, 4 runs on average were selected from each of 89 routes for weekdays and 4 runs for each of Saturday and Sunday were selected from each of the 46 routes operating on those days. This involved the printer in setting up approximately 4,500 different masters for the route, run, and trip number combinations. A determination was made to print 60 cards for between three and ten colors according to the route number. Blank red cards were provided to be used as spares, in the event that the printed supply was exhausted. The blank red cards could also be used if the supply of some other color was exhausted. However, the surveyors were required to write the color on the cards before handing them out; this was a rare occurrence.

The remaining element of the survey execution that warrants some explanation is the procedure for changing the cards and return boxes at the end of each segment. Surveyors were instructed to ask the driver to tell them when they were approaching a timing point that corresponded to the boundary between two segments. The first action taken was that the surveyor at the front of the bus put away the remaining unused cards of the current color segment and picked up the next color for the new segment, before starting to hand out cards to boarding passengers. Thus passengers boarding at the stop closest to the timing point would receive cards of the color appropriate for the next segment, into which they would travel immediately. After leaving the stop, all cards retrieved from alighting passengers were placed in the box colored for the segment through which the bus had just passed. Then, a black divider card was placed in the return box, and the box was closed. Finally, the next return box was opened and the transfers obtained from the driver at that stop were placed in the newly opened return box. That meant that the returns from the stop closest to the segment end stayed with the color segment that was in use up to the timing point.

There are two reasons for this process. First, spreading these activities out over the segment transition stop made it easier for the surveyors to undertake the required actions, without confusion and without compromising the other activities required at the stop. Second, it was deemed to be more logical to associate boarding passengers with the just-beginning segment color and alighting passengers with the just-ending segment color, in order to reflect the loading of the route.

ANALYSIS OF RESULTS

The results of the survey are essentially counts of color cards and transfers by the segment color in which each is received. It might be possible to computerize the counting process, but such a procedure was not devised for the Dade County survey effort. Two issues are important to keep in mind in determining how to take the contents of the return boxes and obtain count data from them:

- The returned cards are in reverse order of the trips surveyed (i.e., the top layer of returned cards is from the last trip surveyed and the returned cards in the bottom of the boxes are from the first trip surveyed).
- The returned cards on any given layer in one color box do not necessarily come from the same trip as that layer in a different color box. For example, if the first trip starts midway along the route, the bottom layer of half the boxes will be from Trip 1, while the bottom layer of the other half of the boxes will be from Trip 2.

The procedure developed for analyzing the results was based on a two-step process: first, the trip pattern of the surveyed bus run

METRO-DADE COUNTY ON-BOARD BUS SURVEY: ORIGIN-DESTINATION MATRIX

Route No. 1 Run No. 1 No. of Trips 8

Segment Colors: Red through Yellow Day Thursday1 Weather ___________

RUN DESCRIPTION:

TRIP NO.										
1										
2										
3										
4										
5										
6										
7										
8										
9										
10										
11										
12										

LAYER 1 (TOP) Route No. 1 Run No. 1 Day Thursday1

E N V E L O P E C O L O R (TO SEGMENT)

		RED	GREY	YEL	BLUE	WHITE	GREEN	PINK	TAN	ORANGE	GOLD
C	RED										
A	GY										
R	YEL										
D	BLU										
	WHT										
C	GRN										
O	PNK										
L	TAN										
O	ORN										
R	GLD										

LAYER 2

E N V E L O P E C O L O R (TO SEGMENT)

		RED	GREY	YEL	BLUE	WHITE	GREEN	PINK	TAN	ORANGE	GOLD
C	RED										
A	GY										
R	YEL										
D	BLU										
	WHT										
C	GRN										
O	PNK										
L	TAN										
O	ORN										

FIGURE 4 Example of the counting record form.

was recorded; second, the cards found in each layer in each return box were counted and recorded. An example of the forms used for this is shown in Figure 4. After these forms were filled out, the trip pattern was used to define the trip number of each layer in each color box. Using this key, a matrix was filled out for each trip, as shown in Figure 5. The resulting matrices can be keyed into a microcomputer or mainframe computer for further analysis and for aggregation by time period or other analysis.

The analysis is not instantaneous because of the incidence of potential errors by surveyors, particularly as found by the authors in the case study. These errors lengthen the process of analyzing the results, which must be done by only one or two trained people who will make consistent judgments about the rectification of errors. However, even in the case described here, in which the incidence of error could be expected to be significantly higher than in most cases, it was possible to develop results within about 10 days of execution of the survey for a given route. This represents a quite rapid turn-around of processed data compared with more traditional survey methods.

CASE STUDY

The survey procedure described in the preceding sections of this paper was used in Dade County, Florida, in the early summer of 1985. The purpose was to provide information on the bus system that could be used to plan substantial changes in the bus system while minimizing the potential loss of existing bus users. As noted earlier, Dade County had previously proved a difficult location to survey, partly because of the multiple languages used by the population and partly because bus riders there appear to be little inclined to cooperate in an on-bus survey.

A large sample was selected to provide extensive data on the various time periods. Of particular concern was collection of data on the low-patronage periods, such as the early morning, the late evening, and weekends. This concern dictated a large sample, although good information on the remaining service periods was also desired. The sample selected was generally four bus runs from each route for a weekday, four runs for a Saturday, and four runs for a Sunday. The number of runs operated on bus routes in Miami

METRO-DADE COUNTY ON-BOARD BUS SURVEY: ORIGIN-DESTINATION MATRIX

Route No. ________ Run No. ________ Trip ________

Date ________ Weather ________ Direction ________

B O X C O L O R (TO SEGMENT)

		RED	GREY	YEL	BLUE	WHT	GRN	PINK	TAN	ORN	GOLD	Sub-Total	Not Dist.	Diff-erence
	RED													
C	GREY													
A	YEL													
R	BLUE													
D	WHT													
C	GRN													
O	PINK													
L	TAN													
O	ORN													
R	GOLD													
	TOTAL													

(FROM)

FIGURE 5 Example of the segment-to-segment trip matrix.

ranges from 1 to more than 25. For bus routes with large numbers of runs, more than four runs were sampled. For routes with four or fewer runs, all operated runs were included in the sample.

To a large extent, run numbers are assigned in chronological order beginning with the time at which the bus route first goes into service. Thus low-numbered runs are generally those commencing service early in the morning, and high-numbered runs commence in the late afternoon. Trippers (runs that are operated for only one or two trips) are generally interspersed in the run numbering on the same chronological basis. It was decided therefore to use systematic sampling. The size of the interval for systematic sampling was varied by route, according to the number of runs operated on the route and the desired sample. For example, if a route had 12 runs and a sample of 4 was desired, every third run was picked, with a starting point that was systematically varied between Run 1 and Run 3. The sample generated by this procedure for each route was found to contain trippers and base runs in approximately the same proportions as for the entire route and to have a reasonable distribution of runs by time of day.

It was desired by Dade County that county employees be trained to undertake the on-bus survey work with supervision provided by the consultants who designed the survey. Because the use of county employees involved taking employees away from their normal duties during the survey, a limit of eight 5-hr (approximately) shifts was established. This required that a total of more than 450 employees be trained to conduct the survey. With such a large number of surveyors, there was great difficulty in identifying and correcting surveyors who did not perform correctly and a lack of ability to impose disciplinary action against nonperforming surveyors. It could be expected that this scenario would result in much greater potential for problems than would be the case when the surveyors are hired and trained specifically for the survey, a smaller number of surveyors are used, and retraining and dismissal of surveyors not working correctly are possible.

In execution, a number of mistakes were made by surveyors. However, it was found that many of these mistakes did not compromise survey results, if care was taken in the counting and analysis work. Four of the most common errors made are listed next.

- Surveyors did not change to a new trip box at the end of each trip, so the number of the trip on returned cards did not correspond to the trip on the surveyed run. Provided that the black divider cards were always placed correctly, this generally had no effect on the final data—the trip numbers were simply ignored.
- Surveyors did not always place a black divider card in the return boxes at the end of each segment throughout the trip. If the correct trip boxes had been used, this could generally be corrected by checking the trip numbers printed on the cards.
- Surveyors did not always change trip boxes and did not place black divider cards correctly to identify completion of each segment during each trip. About 50 percent of these cases were recoverable by examining the transfers placed with returned cards (indicating route and time of issue) in conjuntion with the color pattern of the cards. The transfers revealed the trip number and the color pattern revealed whether it was an outward trip or an inward trip (i.e., which half of the matrix was represented).
- Surveyors failed to change survey materials from one run number to the next when the sample included two consecutive runs on the same bus. In such cases, surveyors often continued handing out cards from the earlier run on the new run, going back and using unused cards out of earlier trip boxes. In virtually all such cases, the data could be recovered, provided that cards were at least used in consecutive trip order, and more easily if divider cards were used correctly.

On the basis of the total number of cards of each color that was returned and the number unused for trips on which no errors were made, it appears that the response rate from passengers who accepted cards was generally between 95 and 100 percent. On the basis of an earlier survey that provided on-off counts and some spot checks of the surveyors, it was found that between 90 and 98 percent of passengers accepted cards. Therefore, the overall response rate from this survey was between 85 and 98 percent.

The success of the survey methodology can also be seen in Table 1, which gives the disposition of the final sample in summary form. As can be seen from the table, only four weekday runs and two weekend runs that were surveyed could not be processed into trip matrices. Included in the count of runs cancelled are runs that were sampled but for which it turned out not to be possible to schedule a survey team; runs that were cancelled by the bus operator on the survey day; runs on which the bus broke down and the run did not continue in service; and runs where an error was made in the survey scheduling, which resulted in an inability to get a survey team on the bus in time to do the survey. Overall, completed runs, for which the data could be analyzed and used, represent 86.6 percent of the originally selected weekday sample and 83.4 percent of the weekend sample. Spoilt runs constitute less than 1/2 percent of either weekday or weekend samples.

TABLE 1 SUMMARY OF FINAL DISPOSITIONS OF SURVEY CASE STUDY

Day of Week	Runs Sampled	Runs Completed	Runs Cancelled	Incomplete Runs
Weekday	344	298	42[a]	4
Weekend	349	291	56	2

Source: Schimpeler Corradino Associates.

[a]Includes one run on which there were insufficient data to process—may have been spoilt by the surveyor.

Expansion factors for this survey by time of day ranged between 1.000 and 12.000. Average expansion factors by time of day are given in Table 2. The aim of the survey originally was a 40 percent sample, which would give an average expansion factor of 2.500. Given cancelled runs, the final sample was around 34 percent, which would give an average expansion factor of 2.9. The figures in Table 2 are based on a count of the trips within each run for which data were usable and is, therefore, based on more precise numbers than route-by-route. Also, the disaggregation by time of day adds precision to the data. It is clear that each period of the day averaged a quite similar expansion factor, with only the early morning and morning peak exceeding the average 2.9 factor. More important, the late evening (6 p.m. to 2 a.m.) has one of the lowest expansion factors, at 2.692, with a low standard error of 1.815. Assuming that expansion factors are t-distributed, 95 percent of expansion factors by period of the day lie between 1.000 and 7.30 for any period. For most periods, the range is much narrower than this. The average of these expansion factors is lower than the expected 2.9, largely because runs that were cancelled for lack of surveyors were chosen as far as possible to be runs with the fewest trips from the sample for each route. Also, it is apparent that

TABLE 2 AVERAGE OF ROUTE-BY-ROUTE EXPANSION FACTORS BY TIME OF DAY

Factor	Time of Weekday					Saturday	Sunday
	4 a.m.–7 a.m.	7 a.m.–9 a.m.	9 a.m.–4 p.m.	4 p.m.–6 p.m.	6.p.m.–2 a.m.		
Average	3.166	3.096	2.422	2.897	2.692	2.247	2.261
Minimum	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Maximum	11.500	11.000	8.000	12.000	9.000	5.455	5.526
Standard error	2.100	2.332	1.526	2.012	1.815	1.540	1.460

Source: Schimpeler Corradino Associates.

approximately the same level of accuracy was achieved, in terms of sampling rate of bus trips, for each time period of interest. Overall, Tables 1 and 2 point to a successful survey that achieved the desired sampling accuracy.

CONCLUSIONS

An on-board bus survey procedure is described that allows collection of data about the origin-destination pattern of use of each bus route in a system, together with limited data on transfer patterns. These data, typically only available by questioning bus passengers, can be obtained through this on-board bus survey procedure without requiring passengers to respond to questions. The survey is of particular value in locations where significant numbers of bus patrons may be unable to speak English or are insufficiently fluent in English to be able to deal with an interview or self-administered form. The procedure is a simple one that requires the passenger to accept a colored, imprinted card when boarding the bus, hold the card during his trip, and return the card on alighting from the bus. The potential response rate is quite high, with the case study presented in this paper indicating an achievable response of from 85 to 98 percent on a route-by-route basis in a location that had previously proved to be highly resistant to on-board bus surveys. The survey execution is sufficiently simple that a large number of surveyors could be trained to conduct the survey and do so with a quite low error rate.

The analysis procedures for the survey results are simple and can be executed rapidly, which allows results to be obtained within a matter of days or weeks of survey execution compared with the months more normally encountered in traditional on-board surveys. Although the initial recording activities for the survey results are manual and comparatively time consuming, the rate of obtaining survey results compares favorably with most surveys, and the counted data are readily analyzed on either a microcomputer or a mainframe computer.

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REFERENCES

1. I. M. Sheskin and P. R. Stopher. "Surveillance and Monitoring of a Bus System." In *Transportation Research Record 862*, TRB, National Research Council, Washington, D.C., 1982, pp. 9–15.
2. J. Attanucci, I. Burns, and N. Wilson. *Bus Transit Monitoring Manual.* Report UMTA–IT–09–9008–81–1. UMTA, U.S. Department of Transportation, Vol. 1, Aug. 1981.
3. P. R. Stopher. "The Design and Execution of On-Board Bus Surveys: Some Case Studies." *Proc., Second International Conference on New Survey Methods in Transport*, Hunter Valley, New South Wales, Australia (in press).
4. J. Simon and P. G. Furth. Generating a Bus Route O-D Matrix from On-Off Data. *Journal of Transportation Engineering Division*, ASCE, Vol. 111, No. 6, 1985, pp. 583–593.
5. I. M. Sheskin, G. S. Spivack, and P. R. Stopher. The Dade County On-Board Survey. *Transit Journal*, Spring 1981, pp. 15–28.
6. Schimpeler Corradino Associates. *Florida Statewide Transit Assessment and Impact Analysis.* Working Paper 1. Florida Department of Transportation, Tallahassee, Aug. 1982.
7. P. R. Stopher. Data Needs and Data Collection—State of the Practice. In *TRB Special Report 201: Travel Analysis Methods for the 1980s*, TRB, National Research Council, Washington, D.C., 1983, pp. 63–71.

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Selectivity Bias in Models of Discrete and Continuous Choice: An Empirical Analysis

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In this paper is discussed an application of a recently developed econometric technique for correcting selectivity bias in discrete and continuous modeling systems with multiple discrete choices. The case studied is the household's choice of type of vehicle to own and the extent to which it is utilized. An appropriate model structure is formulated, and vehicle utilization equations that do and do not account for selectivity bias are estimated. The empirical results strongly underscore the importance of proper econometric treatment of discrete and continuous modeling systems.

In recent years there has been considerable research examining behavioral choices that involve jointly determined discrete and continuous components. One of the primary factors motivating such research is the relatively frequent occurrence of discrete and continuous interrelationships in actual choice situations. Typical examples include the choice of durable goods, such as an appliance or automobile (i.e., discrete), and the extent to which it is used (i.e., continuous), occupation choice and resulting income, union participation and earnings, and the choice of freight mode and quantity shipped.

From an econometric standpoint, the modeling of discrete and continuous choices presents a number of interesting implications. Perhaps the most important is the sample selection or selectivity bias that will be present in the continuous equations. To address this problem, Heckman *(1-3)*, Schmidt and Strauss *(4)*, Westin and Gillen *(5)*, Duncan *(6)*, and McFadden and Winston *(7)* have all developed or applied, or both, corrective econometric techniques. Essentially, such corrective methods involve the joint estimation of a discrete model, traditionally derived from random utility theory (e.g., probit or logit), and a continuous model, normally estimated by regression procedures. Unfortunately, most existing studies on this subject are based on econometric methods that make extensions beyond the consideration of simple binary discrete choices exceedingly difficult, if not impossible.

In this paper is demonstrated, by empirical example, a recently derived method *(8, 9)* of correcting selectivity bias in discrete and continuous modeling systems with multiple discrete choices. The objective here is not to develop new econometric theory or methods but to make recent econometric contributions in the area of selectivity bias more widely known.

SELECTIVITY BIAS PROBLEM

Virtually any modeling system that has interrelated discrete and continuous choices will exhibit selectivity bias in its estimation of continuous equations. To illustrate this, the household decision of type of vehicle to own and the extent to which it is utilized will be assessed. This particular decision process has recently been recognized as a classic example of interrelated discrete and continuous choice *(10–12)*.

For the purposes of this paper, consider households owning only one vehicle and choosing among three types of vehicles that are defined as *(a)* vehicles with less than 25,000 accumulated mileage, *(b)* vehicles with accumulated mileage between 25,000 and 60,000 mi, and *(c)* vehicles with accumulated mileage in excess of 60,000 mi. These mileage classifications are loosely based on observed utilization behavior and annual maintenance and repair costs, although a rigorous statistical classification along these lines would be a preferred approach. Also, by restricting the analysis to households owning only one vehicle, the problems associated with assigning utilization among household vehicles is avoided. For models that explicitly address this multivehicle utilization assignment problem see the work of Mannering *(13)* and Greene and Hu *(14)*.

Intuitively, a basic understanding of the selectivity bias problem, as it relates to vehicle usage, can be gained by noting that usages are observed only for the vehicle type actually selected by the household, and no information is available on the extent to which other vehicle types would have been used by the household had they been selected. As an example of the selectivity bias that can result from such a problem, consider Figure 1. Let Line a represent a least squares estimation of an equation that is defined for the low accumulated mileage vehicle type, assuming that usage data on the low-mileage vehicle type is available for all households. In reality, the observed sample of low-mileage vehicle type users is composed primarily of high-usage households that have selected the low accumulated mileage vehicle type for reasons such as the pleasure of driving a newer automobile and the need for vehicle reliability. Therefore, using the realistic observed sample, a least squares equation estimation will produce bias parameter estimates as reflected by Line b of Figure 1.

To formalize this selectivity bias from an econometric standpoint, it is necessary to consider the problem as a correlation of residuals. To illustrate this, consider a utility-maximizing modeling system defined for each household (j) such that, for discrete choice of vehicle type,

$$U_{ij} = \theta_i Z_{ij} + \varepsilon_{ij} \tag{1}$$

where

- U_{ij} = total indirect utility provided by vehicle type i,
- Z_{ij} = a vector of household and vehicle type attributes,
- ε_{ij} = a disturbance term accounting for unobserved effects, and
- θ_i = a vector of estimable parameters.

For continuous choice of household vehicle utilization,

$$y_{ij} = \beta_i X_j + \nu_j \tag{2}$$

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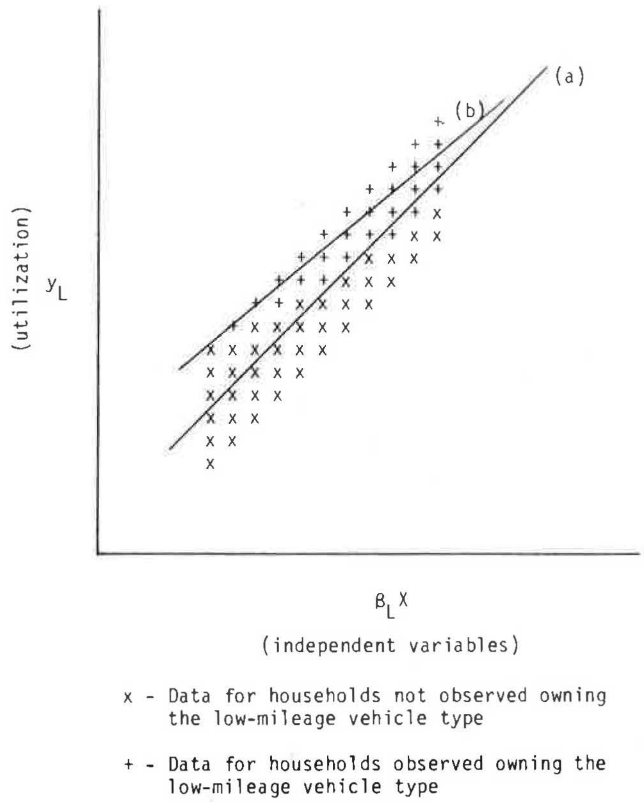

FIGURE 1 Illustration of the selectivity bias problem.

where

y_{ij} = household utilization of vehicle type i (e.g., miles per year);
X_j = vector of household socioeconomic conditions;
v_j = unobserved characteristics of the household; and
β_i = a vector of estimable parameters that vary across vehicle types (i's).

Econometrically, the problem of selectivity bias arises because correlation is likely to be present between the unobservables ε_{ij} and μ_j [i.e., $E(\varepsilon_{ij} v_j) \neq 0$]. For example, the unobserved effects that tend to increase usage (e.g., household's value of driving pleasure) will adversely affect the probability of owning a vehicle that has high accumulated mileage because such a vehicle is likely to be decrepit and therefore provide little driving pleasure. Similarly, the unobserved effects that increase the utility of selecting a low-mileage vehicle (e.g., need for reliability in travel) are likely to be associated with a higher degree of vehicle usage.

If correlation of error terms does exist, estimation of Equation 2 by ordinary least squares (OLS) will produce biased and inconsistent parameter estimates. This follows because such correlation implies that households observed to own specific vehicle types (i.e., low accumulated mileage) may indeed be a nonrandom sample that is censored by usage, a dependent variable.

Alternatively, estimating a single vehicle utilization equation with dummy variables that indicate the choice of vehicle type may be considered. However, this too would result in biased and inconsistent parameters because the dummy variables would most assuredly be correlated with the disturbance term (e.g., a low-mileage car is likely to have a high utilization disturbance term). To effectively correct for selectivity bias, it is necessary to estimate vehicle utilization equations as part of a joint model that includes the discrete choice of vehicle type.

Econometric Methods

To resolve the selectivity bias problem and arrive at consistent estimates of the parameters that comprise the utilization equations, Equation 2 is written as

$$E(y_{ij} \mid i) = \beta_i X_j + E(v_j \mid i) \tag{3}$$

where $E(y_{ij} \mid i)$ is the utilization conditional on the choice of vehicle type i; $E(v_j \mid i)$ is the conditional unobserved household characteristics; and other terms are as previously defined.

The estimation of Equation 3 will provide bias-corrected and consistent estimates of the parameter vector (β) because the selectivity bias induced by the nonrandom observed utilization samples is explicitly accounted for by the conditional expectation of v_j [i.e., $E(v_j \mid i)$]. The problem in estimating Equation 3 becomes one of obtaining a closed-form representation of $E(v_j \mid i)$ that can be used in equation estimation. Such a closed-form representation has been derived by both Hay *(8)* and Dubin and McFadden *(9)*, on the assumption that the discrete choice can be represented by a multinomial logit model. The general form of the derivation is as follows (suppressing the household subscripting for notational convenience).

Let γ denote the vector of discrete choice disturbance terms ($\varepsilon_1, \varepsilon_2, \ldots \varepsilon_K$) where K is the total number of alternatives. It follows that the expectation of v conditional on the choice of i can be written as

$$E(v \mid i) = (1/P_i) \int_{\gamma \mid i} E(v \mid \gamma) \prod_{k=1}^{K} f(\varepsilon_k)\, d_\gamma \tag{4}$$

where P_i is the probability of selecting Alternative i. If it is assumed that γ is generalized extreme value distributed with σ^2 denoting the unconditional variance of v and ρ_i denoting the correlation of v and the resulting discrete choice logistic error terms (i.e., $\varepsilon_i - \varepsilon_k$'s), Hay *(8)* has demonstrated [see also Dubin and McFadden *(9)* and Dubin *(15)*] that Equation 4 can be written as

$$E(v \mid i) = (-1)^{K+1} (\sigma\, 6\, \rho_i/\pi^2) \Big((1/K) \sum_{k \neq i}^{K} \{[P_k \ln P_k/(1 - P_k)] + \ln P_i\}\Big) \tag{5}$$

Thus the selectivity bias correction becomes a simple ratio of the multinomial logit discrete choice probabilities.

Therefore, to obtain utilization equations free from selectivity bias, the following estimation procedure is used:

1. Estimate a multinomial logit model of vehicle type choice.
2. Use the predicted type choice probabilities (P_{kj}'s) to arrive at consistent estimates of the selectivity bias correction represented by the portion of Equation 5 in large parentheses.
3. With the values from Step 2, estimate Equation 3 by OLS; note here that the $\sigma\rho_i/\pi^2$ term in Equation 5 becomes an estimable OLS parameter.

An empirical application of the procedure is presented later.

Model Structure

Before proceeding with the actual estimation, it is necessary to provide a more detailed representation of the model structure than that given in Equations 1 and 2. To begin, let the household's vehicle choice indirect utility function be

$$U_{ij} = \theta_i Z_{ij} + \phi y_{ij} + \varepsilon_{ij} \tag{6}$$

where y_{ij} is the household utilization of vehicle type i; ϕ is an estimable parameter; and other terms are as defined for Equation 1. The inclusion of y_{ij} in the indirect utility function reflects, logically, the significance of vehicle utilization in determining the choice of vehicle type. However, because y_{ij} is endogenous to the type choice process and observed for only the chosen vehicle type, the reduced form of the indirect utility function must be used such that (by substitution of Equation 2),

$$U_{ij} = \theta_i Z_{ij} + \phi \beta_i X_j + \phi \nu_j + \varepsilon_{ij} \tag{7}$$

If the ε_{ij}'s are generalized extreme value distributed, then the type choice probabilities are given by the standard multinomial logit model

$$P_{i'j} = e^{V_{i'j}} / \sum_i e^{V_{ij}} \tag{8}$$

where $P_{i'j}$ is the probability of household j selecting vehicle type i' and V_{ij} is the deterministic component of the indirect utility U_{ij} (i.e., all terms except ε_{ij}). Note here that because the error term $\phi\nu_j$ (see Equation 7) does not vary across vehicle alternatives (i's), it will not affect the assumption of a logit model structure.

With this model structure, it follows that the selectivity bias corrected utilization equations are of the estimable form,

$$y_{ij} = \beta_i X_j + \alpha_j \lambda_{ij} + \eta_i \tag{9}$$

where

$\alpha_i = (-1)^{K+1} (\sigma\ 6\rho_i/\pi^2)$, a parameter estimable by OLS,

and

$$\lambda_{ij} = (1/K) \sum_{k \neq i}^{K} \{[P_{kj} \ln P_{kj}/(1 - P_{kj})] + \ln P_{ij}\}$$

It is important to note here that, to improve exposition of forthcoming empirical results, ρ_i is not included in the summation over K. This exclusion implies an equality restriction, across choice alternatives, of the correlation of ν and $\varepsilon_i - \varepsilon_k$'s. Relaxation of this restriction complicates the model structure by making additional parameter estimation necessary (i.e., a total of $K - 1$ α's must be estimated for each i). However, it has been empirically demonstrated that such a restriction of ρ_i is not unreasonable (*8*).

As described earlier, OLS estimates of Equation 9 will result in consistent parameter estimates. An empirical demonstration is presented in the following section.

Estimation Results

As described earlier, the empirical analysis considers single-vehicle households that own low, medium, or high accumulated mileage vehicles. The data used for model estimation consisted of a 364-household sample collected by the U.S. Department of Energy in the spring of 1980. Utilization of the vehicles owned by these households is defined as the mileage accumulated over the 6-month period from January 1980 to June 1980. Of these 364 households, 81, 185, and 98 owned low-, medium-, and high-mileage vehicles, respectively. A complete list of variables used in subsequent estimations, along with the corresponding means and standard deviations associated with the household sample, is given in Table 1.

Turning first to the estimation of the multinomial logit vehicle type choice model, it was found that vehicle capital cost, age of the head of the household, household income, residential location, number of household members, and number of drivers in the household all entered the reduced form indirect utility function as specified by Equation 7. The resulting coefficient estimates are given in Table 2.

TABLE 1 VARIABLES USED IN MODEL ESTIMATION

		Mean		
Variable	Mnemonic	Low Mileage	Medium Mileage	High Mileage
No. of miles driven in 6-month period (dependent variable in utilization equations)	y	4908.1 (3220.8)[a]	4681.7 (4706.6)	2836.3 (2670.9)
Age of household head (yr)	AGE	45.0 (17.9)	47.5 (18.8)	52.6 (20.5)
Location indicator (1 if SMSA, 0 otherwise)	SMSA	0.77 (0.43)	0.68 (0.47)	0.66 (0.48)
No. of drivers in household	NDRIV	1.52 (0.62)	1.43 (0.66)	1.34 (0.61)
Household income ($/yr)	INC	18,723 (11,800)	15,520 (12,517)	11,396 (8,112)
Vehicle capital cost ($)/income ($/yr)	COST	0.809 (0.826)	0.404 (0.413)	0.116 (0.118)
No. of household members	NMEM	2.40 (1.21)	2.33 (1.34)	2.35 (1.47)
Selectivity bias correction[b] (λ)	SBC	−1.31 (0.30)	−0.75 (0.077)	−1.15 (0.354)

[a]Standard deviations in parentheses.
[b]As defined in Equation 9.

TABLE 2 MULTINOMIAL LOGIT VEHICLE TYPE CHOICE ESTIMATES

Variable	Estimated Coefficient	t-Ratio
Cost (Alt1, Alt2, Alt3)	−0.835	−2.16
AGE (Alt1)	−0.019	−2.13
AGE (Alt2)	−0.04	−1.89
INC (Alt1)	3.23 E-05	1.56
INC (Alt2)	2.47 E-05	1.40
SMSA (Alt1)	0.296	0.83
SMSA (Alt2)	−0.108	−0.39
NMEM (Alt1)	−0.209	−1.49
NMEM (Alt2)	−0.159	−1.40
NDRIV (Alt1)	0.253	0.87
NDRIV (Alt2)	0.111	0.46
Constant (Alt1)	0.725	0.82
Constant (Alt2)	1.551	2.26

Note: Alt = alternative, Alt1 = low mileage (less than 25,000 accumulated miles), Alt2 = medium mileage (25,000 to 60,000 accumulated miles), and Alt3 = high mileage (more than 60,000 accumulated miles). Variable coefficient value is defined only for those alternatives listed in parentheses and is zero for nonlisted alternatives. Number of observations = 364; log-likelihood at zero = −339.9 and at convergence = −327.4.

The estimates are of plausible sign and reasonably significant statistically. It is interesting to note the importance of the age and income variables in determining vehicle type choice. These results reflect a propensity, as expected, of young, high-income households to own low-mileage vehicles. Also, the vehicle capital cost variable produced an anticipated strong negative effect on vehicle type choice probabilities.

It is important to note that the model presented in Table 2 represents the best specification obtained from a large number of estimation trials. Other model specifications tested resulted in substantially lower t-statistics or lower log-likelihoods at convergence, or both. On the basis of this assessment, the model presented herein can be presumed to be fairly well specified. The issue of proper specification is potentially important because a seriously misspecified model can lead to erroneous interpretations of the magnitude of selectivity bias (*8*).

Given the specification of the type choice model presented in Table 2, the selectivity bias correction can be readily determined (see Equation 9).The means and standard deviations of the resulting selectivity bias corrections are given in Table 1. It is interesting to point out that the selectivity bias term in Equation 9 (see also Equation 4) will be higher (in absolute value) for a specific alternative when the probability of a household selecting that alternative is lower. This is intuitively reasonable because it is expected that the estimated coefficients (the β_i vector) will require greater correction when the household's vehicle selection probability is low.

With the calculated selectivity bias terms in hand, utilization equations for low, medium, and high accumulated mileage vehicles can be estimated. The estimations include the natural log of utilization as the dependent variable with head of household's age, residential location, number of household drivers, and income as independent variables. The natural logarithm of utilization was used to improve statistical fit and to avoid the possibility of negative predicted values. Note that, by using ln y_{ij} in place of y_{ij} in all equations, the modeling system represented by Equations 7–9 is still valid. Also, it should be mentioned that the independent variables incorporated in this model are similar to those used by Mannering (*12, 13*) and Greene and Hu (*14*). Previously, however, only Greene and Hu estimated different coefficients for different vehicle types, and their work ignores possible selectivity bias. Finally, note that the utilization equations do not contain any vehicle-specific attributes. As demonstrated by Heckman (*2*, pp.935–936), this is a necessary condition for the existence of the model as defined by Equations 7–9.

Table 3 gives the estimation results for equations not corrected for selectivity bias and for those that are corrected for selectivity bias. The results indicate that the age variable has a strong negative effect on vehicle utilization in all equations. In addition, residential location and the number of household drivers were found to provide generally reasonable but less significant coefficient estimates. The income variable was generally not significant, and this was particularly true for those equations that were corrected for selectivity bias. Overall, the differences between corrected and uncorrected coefficients, though noticeable, are not large when the corresponding standard errors are considered. It is speculated that larger sample sizes would produce more statistically significant differences between corrected and uncorrected model coefficients.

Turning specifically to the selectivity bias terms, it is notable that the selectivity bias coefficients were highly significant in the medium- and high-mileage utilization equations. This is a strong

TABLE 3 UTILIZATION EQUATION ESTIMATES, UNCORRECTED AND CORRECTED FOR SELECTIVITY BIAS

	Low Mileage		Medium Mileage		High Mileage	
Variable	Uncorrected	Corrected	Uncorrected	Corrected	Uncorrected	Corrected
AGE	−0.014	−0.012	−0.017	−0.012	−0.016	−0.011
	(−3.27)	(−2.13)	(−4.95)	(−3.26)	(−3.18)	(1.87)
SMSA	−0.186	−0.287	−0.267	−0.035	−0.255	−0.234
	(−1.01)	(−1.36)	(−1.90)	(−0.230)	(−1.25)	(−1.15)
NDRIV	0.187	0.151	0.102	0.125	0.066	−0.004
	(1.42)	(1.11)	(1.02)	(1.28)	(0.03)	(0.02)
INC	−6.75 E-06	−1.35 E-06	1.07 E-05	3.11 E-06	1.87 E-05	−5.56 E-06
	(−0.98)	(−0.37)	(1.99)	(0.55)	(1.44)	(−0.26)
Constant	8.91	9.64	8.74	11.15	8.31	7.42
	(25.54)	(11.48)	(32.61)	(14.92)	(18.94)	(9.97)
SBC		0.467		3.66		−0.784
		(1.06)		(3.44)		(−1.65)
R^2	.175	.185	.168	.220	.159	.178
Corrected R^2	.131	.131	.150	.198	.123	.134
No. of observations	81		185		98	

Note: Dependent variable is the natural log of miles driven in 6 months (t-statistics in parentheses).

TABLE 4 PERCENTAGE DIFFERENCE BETWEEN CORRECTED AND UNCORRECTED HOUSEHOLD VEHICLE UTILIZATION EQUATION PREDICTIONS

	Low Mileage	Medium Mileage	High Mileage
Average of all households	5.9	13.4	9.9
Standard deviation of all households	9.1	14.0	7.9
Highest difference	53.2	82.1	47.2

indication that sample selectivity bias is present in such equations because the null hypothesis of no selectivity bias can be tested directly using the *t*-statistics of the estimated selectivity bias coefficient (i.e., under the null hypothesis of no selectivity bias, the selectivity bias coefficient would be zero). The selectivity bias coefficient in the low-mileage utilization equation, although of reasonable magnitude, was not highly significant. This may have been caused by the relatively low number of observations or the diversity of households owning low-mileage vehicles, or both. As a final point, it is important to note that the standard errors of the coefficient estimates presented in Table 3 will be biased downward, to some extent, because estimates of the discrete choice probabilities are used in the selectivity bias correction term as opposed to the true probabilities. This obviously results in an upward bias in reported *t*-statistics.

To demonstrate the potential importance of selectivity bias in household vehicle utilization equations, utilization was predicted for low-, medium-, and high-mileage vehicles for all 364 households, using both corrected and uncorrected equations. A summary of the results is given in Table 4. The data in this table indicate that, by ignoring selectivity bias, substantial errors can be introduced into predictions of household vehicle utilization. In the case presented here, it was found that as much as an 82 percent difference between predicted values can result.

CONCLUSION

As demonstrated by the empirical analysis undertaken in this paper, the problem of selectivity bias in the continuous equations of discrete and continuous modeling systems can have significant consequences. Specifically, if selectivity bias is ignored, substantial errors in equation estimation may result. It is therefore essential that proper econometric treatment be given to discrete and continuous modeling systems to ensure the credibility of resulting parameter estimates.

REFERENCES

1. J. Heckman. The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models. *Annals of Economic and Social Measurement*, Vol. 5, No. 4, 1976.
2. J. Heckman. Dummy Endogenous Variables in a Simultaneous Equation System. *Econometrica*, Vol. 46, No. 6, 1978.
3. J. Heckman. Sample Selection Bias as a Specification Error. *Econometrica*, Vol. 47, No. 1, 1979.
4. P. Schmidt and R. Strauss. The Effect of Unions on Earnings and Earnings on Unions: A Mixed Logit Approach. *International Economic Review*, Vol. 17, No. 1, 1976.
5. R. Westin and D. Gillen. Parking Location and Transit Demand: A Case Study of Endogenous Attributes in Disaggregate Model Choice Models. *Journal of Econometrics*, Vol. 8, 1978.
6. G. Duncan. Formulation and Statistical Analysis of Mixed, Continuous/Discrete Dependent Variable Model in Classical Production Theory. *Econometrica*, Vol. 48, No. 4, 1980.
7. D. McFadden, C. Winston, and A. Boersch-Supan. "Joint Estimation of Freight Transportation Decisions Under Non-Random Sampling." In *Analytic Studies in Transport Economics* (A. Daugherty, ed.), Cambridge University Press, New York, 1986.
8. J. Hay. *Occupational Choice and Occupational Earnings*. Ph.D. dissertation. Yale University, New Haven, Conn., 1980.
9. J. Dubin and D. McFadden. An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. *Econometrica*, Vol. 52, 1984.
10. K. Train and M. Lohrer. "Vehicle Ownership and Usage: An Integrated System of Disaggregate Demand Models." Presented at 62nd Annual Meeting of the Transportation Research Board, Washington, D.C., 1983.
11. F. Mannering and C. Winston. A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization. *The Rand Journal of Economics*, Vol. 16, No. 1, 1986.
12. F. Mannering. A Note on Endogenous Variables in Household Vehicle Utilization Equations. *Transportation Research*, Vol. 20B, No. 1, 1986.
13. F. Mannering. An Econometric Analysis of Vehicle Use in Multivehicle Households. *Transportation Research*, Vol. 17A, No. 3, 1983.
14. D. L. Greene and P. S. Hu. "The Influence of the Price of Gasoline on Vehicle Use in Multivehicle Households." In *Transportation Research Record 988*, TRB, National Research Council, Washington, D.C., 1984, pp. 19–24.
15. J. Dubin. *Economic Theory and Estimation of the Demand for Consumer Durable Goods and their Utilization: Appliance Choice and the Demand for Electricity*. Ph.D. dissertation. Massachusetts Institute of Technology, Cambridge, 1982.

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Day-of-the-Week Models of Shopping Activity Patterns

MOSHE HIRSH, JOSEPH N. PRASHKER, AND MOSHE BEN-AKIVA

Most empirical studies that deal with activity analysis develop models of daily activity patterns in which the model is assumed to represent all of the days of the workweek. An alternative approach, in which activity pattern models are developed separately for each day of the workweek, is presented. The underlying assumption is that the appropriate basic time unit for analyzing some activity patterns is the week not the day. By applying this approach, a better representation of the behavior of individuals and improved models of activity patterns can be achieved. This hypothesis is tested by developing independent models of daily activity patterns for each day of the workweek and comparing them among themselves and with an average-day model of shopping behavior. The results vary systematically during the week and thus encourage the development of day-of-the-week models for analyzing activity and travel patterns. Furthermore, predictions based on average-day models were found to be biased when used in analyzing a specific day of the week.

Most empirical studies that deal with activity analysis develop models of daily activity patterns, in which the model is assumed to represent all of the days in the workweek. An alternative approach, in which activity pattern models are developed separately for each day of the workweek, is presented. The underlying assumption is that the appropriate basic time unit for analyzing some activity patterns is the week, rather than the day. By applying this approach, better representation of individuals' behavior and improved models of activity patterns can be achieved. The rationale for this approach is discussed in the following section.

BEHAVIORAL FRAMEWORK

Most of the current activity pattern models use the average day as the basic time unit for analyzing activity patterns. This approach requires certain assumptions, two of which have been examined and placed in doubt in this paper:

- An individual's daily activity is habitual; that is, it repeats from day to day *(1)*.
- If day-to-day variability does exist, it is random rather than systematic.

These assumptions appear to be an oversimplification and have been questioned in several studies *(2–5)*. Hanson and Huff *(2)*, for example, examined the day-to-day variability in behavior in Sweden by using trip diaries that covered 35 consecutive days. Their findings show that although daily behavior does have a certain degree of regularity, it is not repetitive. Moreover, even though the working men in the sample exhibit a considerable amount of regularity with respect to their working pattern, it becomes evident that they exhibit considerable day-to-day variability in their discretionary activities.

Prashker and Hirsh *(5)* collected weekly activity diaries in Israel in order to study the differences in daily activity patterns. Their analysis of the average household daily trip rate and the average household daily time for various activities by day of the week revealed three main periods in the week: (*a*) Sunday through Thursday, (*b*) Friday, and (*c*) Saturday. This pattern reflects the structure of business in Israel where Sunday through Thursday are the prime business days, Friday is a reduced-hours workday, and Saturday is the day of rest. Further, significant differences were manifested among the first 5 days of the week. For example, there was a significant reduction in shopping intensity on Tuesday and a similar reduction in personal business on Wednesday.

Whereas the studies just cited tried to identify day-to-day variability, Herz *(4)* attempted to find time cycles within which variability is systematic. To do so, he used daily activity records evenly spread throughout the year, collecting from each individual data for 1 day only. Using aggregate data, Herz found that, aside from the high variability that exists among individuals for the average day, there is a systematic, day-to-day variability, which can be explained by the weekly cycle.

These empirical works provide evidence that day-to-day variability does exist and that it has a strong systematic component. Theoretical works that describe human behavior *(6,7)* place great importance on temporal constraints, and these are also found in empirical work *(8)*. Most temporal constraints are derived from the opening times of institutions and firms. These constraints define the times within which the individual can perform out-of-home activities. As usually happens in an urban system, opening hours do not have a regular daily cycle. In Israel, for example, public health services are closed on Monday and Thursday afternoons; most commercial shops are closed on Tuesday afternoons; banks are closed on Wednesday afternoons; and most schools and working places, especially those involved in services, have different working times on different days. Finally, most institutions and firms in Israel are closed on Friday afternoons and all of them are closed all day Saturday.

Another aspect of the temporal dimension of an individual's activity pattern is his free time. Daily free time is limited, and because each activity needs time for its execution, one activity is performed at the expense of other activities, which have to be postponed to other days.

More recently, Pas and Koppelman *(9)* studied multiday activity patterns using the 1973 Reading Activity Diary Survey. In this study, daily activity patterns were characterized by (*a*) the number of stops in the pattern; (*b*) the stops' purposes (subsistence, maintenance, or leisure); and (*c*) the time of day of the stops (morning or afternoon, peak or off-peak). Using this broad description of activity pattern, five daily patterns were identified for employed persons during the workweek. The study could not reject the null hypothesis that daily pattern selection is independent of the day of the week because of the small sample used. However, some spe-

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cific differences among days do exist. These researchers also showed that empirical results were consistent with the hypothesis that daily activity pattern is the outcome of a two-stage process: (*a*) selection of a multiday pattern and (*b*) selection of a daily pattern based on the multiday pattern.

In this paper is studied the day-to-day variability in the patterns of a single activity—shopping. The main hypothesis is that shopping behavior is dependent on the day of the week and that systematic day-to-day variability in shopping patterns does exist because of systematic variation in the temporal constraints set. This hypothesis is tested by developing models of daily shopping patterns for (*a*) each day of the week and (*b*) an "average" day of the week. The models are then compared in order to find any systematic day-to-day variability in shopping behavior.

The daily models developed in this paper do not include dynamic effect (i.e., they are estimated independently of the individual's behavior on any other day of the week). However, it may be assumed that a single maintenance activity that does not have to be performed every day on a regular basis will be executed only when the need for it exceeds some threshold value. Thus current shopping behavior may be interrelated with past activity patterns as well as with current-day characteristics and with future activity plans. Such an approach is used by Hirsh et al. *(10)*.

DESCRIPTION OF MODEL

During weekdays in Israel (Sunday to Friday) most stores are open from 8:00 a.m. to 1:00 p.m. and from 4:00 p.m. to 7:00 p.m. Some of the big department stores, however, are open continuously from 8:00 a.m. to 7:00 p.m. On Tuesday most stores close at 3:00 p.m. or 4:00 p.m. to comply with a municipal law, although the big department stores do not obey the law and remain open continuously until 7:00 p.m. On Friday most stores are open continuously and their closing time varies between 2:00 p.m. and 7:00 p.m. In this paper the daily shopping pattern assumed to be available for each individual during a weekday is one of the following: (*a*) to not shop that day, (*b*) to shop starting in the morning period (8:00 a.m. to 1:00 p.m.), or (*c*) to shop starting in the afternoon period (after 1:00 p.m.). The alternative of shopping in both periods is not considered separately because of the small number of individuals (only eight) who chose it. This alternative is included in the second one (i.e., starting to shop during the morning period).

The econometric models are based on utility-maximizing principles to describe the individuals' choices among the alternatives. For convenience, it was assumed that the distribution of the error term in the utility function of the daily shopping pattern is in accordance with the assumptions used by the logit-type models. Thus, because the choice set of each individual in each day contains more than two alternatives, the first statistical test examined the feasibility of applying the multinomial logit (MNL) model by testing the independence of irrelevant alternatives (IIA) assumption. In this case it is reasonable to asume that the individual considers the two alternatives of participation (morning or afternoon) to be more closely related than the alternative of not participating. The test is described in detail in Hirsh *(11)*, and it involved calibrating the MNL with all subsets of the alternatives. The IIA test showed that the trinomial structure has to be rejected and replaced by a hierarchical structure, shown in Figure 1, in which the individual first decides whether to shop on that day and then, given a decision to shop, chooses between morning and afternoon. For this structure, a nested logit model was adopted as follows:

$$P(s,d) = P(s) \times P(d|s) \tag{1}$$

where

$P(s,d)$ = the joint probability of selecting a daily shopping behavior,
$P(s)$ = the marginal probability that the individual will choose to shop on that day, and
$P(d|s)$ = the conditional probability of selecting shopping schedule d.

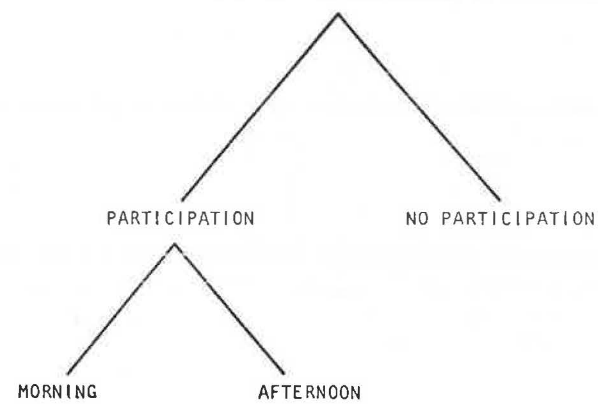

FIGURE 1 Hierarchy of the daily decision-making process.

This structure means that two types of models have to be estimated for each day. The first is a conditional logit model of choice of shopping schedule in the form of

$$P(d|s) = \exp(V_{ds} + V_d)/\sum_t \exp(V_{ts} + V_t) \tag{2}$$

where V_d is the systematic components of the individual's scheduling utility function, which vary only across *d*, and V_{ds} is the systematic components of the individual's scheduling utility function, which vary across *d* and *s*.

In the second stage, a binary logit model of shopping activity participation is estimated in the form of

$$P(s) = \exp(V_s + \tau I_s)/[1 + \exp(V_s + \tau I_s)] \tag{3}$$

where the inclusive utility of shopping is

$$I_s = \ln \sum_t \exp(V_{ts} + V_t) \tag{4}$$

in which τ is the coefficient of the inclusive utility (or log sum variable) and V_s is an additional systematic utility component of the shopping activity that is indepenent of the schedule.

Data were collected in 1983 from 567 individuals, aged 18 and older, in the form of weekly diaries. These individuals, members of 288 households in Israel, included 528 male and female household heads. Using the structure just described, two kinds of models were estimated:

- Day-of-the-week models that assume that an individual's utility function may vary from day to day. The models also assume independence of activity patterns executed on different days of the week.

• The "average-day" model that assumes independence between different days and a constant utility function throughout the week.

Because the average-day models assume independence among days, repeated observations of an individual may be treated as independent. In this case each individual was observed for 6 consecutive days. Using this data set, the average-day models can be estimated in several ways. First, data for only 1 day, selected randomly, can be used for each individual. Second, using all of the days, an average day for each individual can be calculated using the averages of all the relevant attributes. Third, all of the available information may be used if each day is treated as an independent observation. The latter option was selected for the following reasons. First, because the data have already been collected, this option retains the maximum amount of information. Second, because models that use all the observations have been estimated, the day-of-the week models are actually calibrated using subsets of this data. This property makes it possible to compare the two models using some statistical tests that apply to estimation with subsets of the data.

By using this approach, two variants of the average-day models were estimated: one that used data from the first 5 days of the week (Sunday through Thursday) and another that used the first 6 days of the week (Sunday through Friday). These models were estimated because Friday in Israel has significantly different temporal constraints than do the other days. Therefore, although the conventional models developed earlier did not distinguish among the days, this type of estimation made it possible to identify the effect of inclusion of a significantly different day in the average-day group.

At this point it should be noted that neither the day-of-the-week nor the average-day models consider interdependence among days. The average-day model assumes independence of observations, and the day-of-the-week models assume independence of the various models. However, it may be found that a certain degree of dependence does exist among activity patterns executed by the same individual on different days of the week. The neglect of this type of dependency in the models results in a specification error, which may bias the estimates of the maximum likelihood parameters. However, it is assumed that these effects are similar in the average-day and the day-of-the-week models, and hence the comparison of the models is not affected.

ESTIMATION RESULTS

General

Discussion of estimation results will be confined to the main topic of the paper: day-of-the-week models versus average-day models. The two model types will be compared on the basis of statistical t-tests and interpretation of parameters. Both the daily models and the average-day model have been calibrated using an identical specification, as can be seen in Tables 1–4. Tables 1 and 2 give the estimation results for the conditional and the marginal day-of-the-week models, and Tables 3 and 4 give the corresponding results for the average-day models. (The insignificant attributes are retained in the tables in order to allow the statistical comparisons that require identical specification.)

The various attributes used in the models can be categorized under the following two classes: (*a*) those that may change during the week, such as the temporal constraints attributes or the individual's working pattern, and (*b*) those that do not change during the week (socioeconomic variables). The marginal participation mod-

TABLE 1 ESTIMATION RESULTS FOR THE CONDITIONAL DAILY SCHEDULING MODELS

Variable[a]	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday
Dummy for afternoon participation	1.5	0.67	1.5	3.0	1.1	10.27
	(0.7)	(0.3)	(0.7)	(1.6)	(0.5)	(1.6)
Available time for shopping between	-0.01	-0.01	-0.01	-0.01	-0.01	-0.05
8:00 and 13:00	(3.3)	(3.7)	(3.8)	(3.7)	(4.4)	(2.8)
Available time for shopping between	0.01	0.007	0.004	0.006	0.02	-0.007
16:00 and 19:00	(2.1)	(1.5)	(0.9)	(1.1)	(3.1)	(0.5)
Dummy for male head of household	0.72	0.7	0.86	0.68	1.6	-0.05
	(1.5)	(1.3)	(1.5)	(1.4)	(2.8)	(0.07)
Dummy for private car present in house-	-1.7	-1.0	-1.0	-0.6	-0.17	0.6
hold	(2.1)	(1.8)	(1.9)	(1.1)	(0.3)	(0.5)
No. of children under 5	-0.83	0.33	0.25	0.27	-0.4	0.1
	(2.4)	(1.0)	(0.7)	(0.8)	(1.0)	(0.2)
Dummy for being at work on this day	0.9	0.27	-1.6	0.29	0.2	-13.2
	(0.7)	(0.3)	(1.4)	(0.3)	(0.2)	(2.4)
No. of work days in the week	-0.11	0.11	0.13	-0.2	-0.3	0.3
	(0.7)	(0.7)	(0.9)	(1.2)	(1.8)	(1.1)
Time in minutes from home to central	-0.01	0.01	0.02	-0.03	-0.004	-0.01
business district	(0.6)	(0.5)	(1.0)	(1.2)	(0.2)	(0.2)
Time in minutes from home to nearest	0.1	0.05	-0.1	0	-0.04	0.16
food store	(1.5)	(0.6)	(1.3)	(0)	(0.6)	(1.2)
No. of years of study	0.17	0.03	0.01	0.03	0.02	0.18
	(2.3)	(0.5)	(0.2)	(0.5)	(0.3)	(2.1)
Age	-0.07	-0.02	0.02	-0.03	0.002	0.01
	(3.3)	(1.2)	(0.8)	(1.3)	(0.1)	(0.4)
Dummy for households with male head	-0.22	0.41	-2.8	-1.3	-0.5	-0.74
only	(0.2)	0.3	(2.2)	(1.0)	(0.3)	(0.4)
Expected duration of shopping[b]	-0.009	-0.006	-0.02	0.02	0.02	-0.02
	(0.6)	(0.6)	(1.3)	(0.2)	(1.4)	(1.5)
No. of cases	211	213	173	206	205	207
$\mathcal{L}(0)$	-146.3	-147.6	-119.9	-142.8	-142.1	-143.5
$\mathcal{L}(\hat{\beta})$	-83.5	-86.6	-84.1	-95.5	-72.5	-48.2
ρ^2	0.43	0.41	0.30	0.33	0.49	0.66

Note: t-values are in parentheses.

[a]All variables are specific to the afternoon participation alternative except the variable of expected duration of shopping.

[b]This variable was estimated by linear regression for those who shop.

TABLE 2 ESTIMATION RESULTS FOR THE MARGINAL MODELS OF PARTICIPATION IN SHOPPING ACTIVITY

Variable[a]	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday
Dummy for no participation	1.37	2.5	1.8	0.5	3.4	1.5
	(1.4)	(2.5)	(1.8)	(0.4)	(2.9)	(1.0)
Available time for shopping between 8:00 and 13:00	-0.002	-0.002	-0.004	-0.002	-0.002	0
	(0.9)	(0.9)	(1.6)	(1.1)	(1.0)	(0)
Available time for shopping between 16:00 and 19:00	-0.005	-0.006	-0.003	-0.005	-0.001	0.001
	(2.1)	(2.1)	(1.6)	(2.7)	(2.8)	(0.3)
Dummy for male head of household	0.76	0.68	1.1	0.9	0.13	0.4
	(2.9)	(2.1)	(3.2)	(3.8)	(0.3)	(1.8)
Dummy for private car present in household	-0.003	-0.35	0.02	-0.13	0.3	-0.35
	(0.1)	(1.0)	(0.1)	(0.5)	(0.9)	(1.3)
No. of children under 5	-0.2	-0.22	-0.31	-0.1	-0.15	-0.22
	(0.9)	(1.1)	(1.8)	(0.6)	(0.8)	(1.3)
Dummy for being at work on this day	-0.04	-0.42	-1.2	0.12	-1.1	1.1
	(0.07)	(0.8)	(2.0)	(0.2)	(1.9)	(2.0)
No. of work days in the week	0.03	-0.04	0.06	-0.03	-0.04	-0.15
	(0.4)	(0.5)	(0.8)	(0.3)	(0.4)	(2.0)
Time in minutes from home to central business district	-0.007	-0.06	0	0.02	0.02	0.02
	(0.7)	(0.5)	(0)	(1.8)	(1.8)	(1.5)
Time in minutes from home to nearest food store	0.02	0.04	0.02	-0.04	0.02	0.06
	(0.5)	(1.2)	(0.4)	(1.1)	(0.6)	(1.5)
No. of years of study	-0.003	0.02	0.01	0.007	0.008	-0.06
	(0.1)	(0.7)	(0.3)	(0.2)	(0.3)	(1.8)
Age	-0.003	-0.02	-0.006	-0.01	-0.009	0.003
	(0.2)	(0.2)	(0.5)	(1.1)	(0.9)	(0.3)
Dummy for households with male head only	-0.93	-0.9	-1.9	-1.4	-0.6	-1.8
	(1.3)	(1.2)	(2.2)	(1.8)	(0.7)	(2.3)
Log sum of the scheduling conditional model	0.2	-0.07	0.23	0.4	-0.17	-0.8
	(0.6)	(0.2)	(0.7)	(1.0)	(0.7)	(2.4)
No. of cases	507	503	509	504	506	516
$\mathcal{L}(0)$	-351.4	-348.7	-352.8	-349.3	-350.7	-357.7
$\mathcal{L}(\beta)$	-316.8	-315.1	-302.5	-311.9	-314.9	-306.9
ρ^2	0.10	0.10	0.14	0.11	0.10	0.14

Note: *t*-values are in parentheses.

[a]All variables are specific to the alternative of no participation.

TABLE 3 ESTIMATION RESULTS FOR THE POOLED CONDITIONAL SCHEDULING MODELS

Variable[a]	5 Days Pooled	6 Days Pooled
Dummy for afternoon participation	0.5	-0.3
	(0.7)	(0.5)
Available time for shopping between 8:00 and 13:00	-0.01	-0.01
	(8.3)	(8.5)
Available time for shopping between 16:00 and 19:00	0.01	0.01
	(4.2)	(4.6)
Dummy for male head of household	0.8	0.5
	(4.0)	(3.2)
Dummy for private car present in household	-0.7	-0.6
	(3.1)	(3.2)
No. of children under 5	-0.1	-0.09
	(0.7)	(0.8)
Dummy for being at work on this day	-0.02	0.2
	(0.9)	(0.9)
No. of work days in the week	-0.01	0.01
	(0.7)	(0.8)
Time in minutes from home to central business district	0.002	0.003
	(0.3)	(0.4)
Time in minutes from home to nearest food store	-0.02	-0.003
	(0.7)	(0.4)
No. of years of study	0.05	0.04
	(2.0)	(2.0)
Age	-0.02	-0.006
	(2.0)	(1.0)
Dummy for households with male head only	-1.0	-0.9
	(2.1)	(2.1)
Expected duration of shopping[b]	-0.001	-0.004
	(0.1)	(1.0)
No. of cases	1,008	1,215
$\mathcal{L}(0)$	-698.7	-842.2
$\mathcal{L}(\beta)$	-510.4	-666.2
ρ^2	0.27	0.21

Note: *t*-values are in parentheses.

[a]All variables are specific to the afternoon participation alternative except the variable of expected duration of shopping.

[b]This variable was estimated by linear regression for those who shop.

TABLE 4 ESTIMATION RESULTS FOR THE POOLED MARGINAL PARTICIPATION MODELS

Variable[a]	5 Days Pooled	6 Days Pooled
Dummy for afternoon participation	1.9	1.6
	(3.5)	(3.3)
Available time for shopping between 8:00 and 13:00	-0.003	-0.002
	(1.6)	(1.1)
Available time for shopping between 16:00 and 19:00	-0.003	-0.003
	(1.2)	(1.2)
Dummy for male head of household	0.9	0.7
	(5.0)	(4.6)
Dummy for private car present in household	-0.23	-0.15
	(1.4)	(1.0)
No. of children under 5	-0.17	-0.16
	(2.2)	(2.3)
Dummy for being at work on this day	-0.07	-0.02
	(0.3)	(0.08)
No. of work days in the week	-0.05	-0.01
	(0.8)	(0.4)
Time in minutes from home to central business district	-0.006	-0.003
	(1.1)	(0.7)
Time in minutes from home to nearest food store	0.01	0.01
	(0.9)	(1.1)
No. of years of study	0.02	0.009
	(1.3)	(0.6)
Age	-0.01	-0.008
	(2.5)	(1.9)
Dummy for households with male head only	-1.4	-1.3
	(3.7)	(3.8)
Log sum of the conditional scheduling model	0.44	0.2
	(1.5)	(0.6)
No. of cases	2,529	3,045
$\mathcal{L}(0)$	-1753	-2110
$\mathcal{L}(\beta)$	-1589	-1896
ρ^2	0.09	0.1

Note: *t*-values are in parentheses.

[a]All variables are specific to the alternative of no participation.

els also include a log sum variable, which represents the conditional scheduling model described in Equation 4.

In general, the following conclusions can be drawn from the estimation results. First, the results support the hypothesis that the scheduling choice for shopping can be distinguished from the participation choice. This is because the various attributes are found to have different effects on participation and scheduling decisions. This is especially true for the average-day model (Tables 3 and 4) where the free-time attributes are found to influence the scheduling choice but not the participation choice.

The results are less conclusive for the day-of-the-week models of activity patterns. The variables in the daily models (Tables 1 and 2) have different values on different days. However, with few exceptions, the 95 percent confidence interval for many estimates reveals that the null hypothesis, equality of coefficients across the days in the daily models or between the average-day and the daily models, cannot be rejected. Nevertheless, even if the estimated values of the single attributes do not exhibit significant differences across the days, the predicted behavior that results from the daily models can be significantly different from the behavior predicted by the average-day models. This aspect of policy analysis will be demonstrated later in the paper. In the following subsections some of the details of the estimation results are discussed further.

Temporal Constraints Attributes

The category of temporal constraints attributes includes the morning and the afternoon available shopping time for the individual. These attributes are calculated from the individual's reported working pattern and the opening hours of stores in Israel. These are the only attributes, in addition to the individual's working pattern, that change in value during the week. The morning and the afternoon free time are not combined in order to capture the effect of policies such as introducing flexible working hours, which may not change the total free time available to the individual but do change the morning and afternoon free time. Also, in this way the hypothesis that people are using the morning and the afternoon time differently can be tested.

The estimation results for the average-day model show that the free-time attributes are significant to the scheduling decision but not to the participation choice. The daily models, on the other hand, show that the afternoon free time is significant to the participation choice on days when most stores are open in the afternoon (Sunday, Monday, Wednesday, and Thursday). Also, the daily models show that the morning free time on Friday has different value than on the other days, an effect that the average-day models, by definition, cannot show.

Individual and Household Characteristics

The individual characteristics used in the models are the individual's age, education, status in the household, and working pattern. The household characteristics are car availability, number of children, and marital status of the head of household. All of the variables, except the individual's working pattern, remain constant during the week. These variables can also be classified under the following two categories: those that are more related to need for shopping (e.g., number of children) and those that are more related to the individual's ability to shop (e.g., accessibility or working pattern).

The estimation results support the hypothesis that the scheduling decision can be distinguished from the participation decision because some of the variables were found to be significant only to the participation model and others were significant to the scheduling model. However, the variables do perform differently in the average-day and in the daily models. In general, both the scheduling and the participation average-day models exhibit more significant socioeconomic variables than do their corresponding daily models. On the other hand, an individual's working pattern was not found to be significant in the average-day model, but the daily models show that these attributes can be significant to both the scheduling and the participation decisions on some days. The daily models were also able to capture a well-known phenomenon in Israel: Thursday afternoon is the major shopping time for male heads of households. The probable reason for this is that Thursday afternoon is the last opportunity working people (mostly male heads of households in 1982) have to shop for the weekend because stores are closed from Friday afternoon until Sunday morning.

Statistical Comparison

The discussion so far has been based on the interpretation of the models. As was mentioned previously, the average-day model and the day-specific models may be compared by using statistical tests. The average-day conditional scheduling model (Table 3) is calibrated using 1,008 observations from the first 5 days of the week or 1,215 observations from the first 6 days of the week. These are the sum of the observations used in the daily models (Table 1). Because the two model types have the same specification, the following statistic can be used to compare them:

$$-2\,(L_{MP} - \sum_{d} L_{Md}) \qquad (5)$$

where L_{MP} and L_{Md} are the log-likelihood value (at convergence) for the (pooled) average-day model and for day d, respectively. The statistic is distributed chi-squared where the number of degrees of freedom is $(\sum_{d} M_d - M)$ where M is the number of parameters estimated in the pooled model and M_d is the number of parameters in the model for day d.

In this case, the values of this statistic for the daily scheduling models are 391.6 and 176.4 with 70 and 56 degrees of freedom for 6 and 5 days, respectively, which means that the daily scheduling models are significantly different from the average-day scheduling model. However, the null hypothesis of equality of coefficients between the daily and the average-day models cannot be rejected for the marginal participation models for both 5- and 6-day models.

Note also that the two average-day models (the 5- and 6-day models) can be compared. First, using the 95 percent confidence intervals, none of the parameter estimates in either the participation or the scheduling model exhibits significant difference between the 5- and the 6-day models. Also, the values of the statistic in Equation 5 for comparing the 5-day model plus Friday with the 6-day model are almost zero for both the participation and the scheduling models, which implies that there is no significant difference in the parameter estimates between the 5- and the 6-day models. However, given the value of ρ^2, it appears that the 6-day average model is inferior to the 5-day model. This means that the inclusion of a day with a specific temporal constraint system (i.e., Friday) in the calculation of an average model reduces the performance of the average model.

POLICY ANALYSIS

To further illustrate the difference between the two approaches, the average-day and the day-specific models were applied to predict the effect on shopping activity of shortening the workweek in Israel from 6 to 5 days (Sunday through Thursday) and adding 1 work hour to each of the 5 working days. This policy was simulated for 275 individuals in the sample who worked a 6-day week. The policy was reflected in the following attributes of the various models:

- Morning free time—on Friday, this free time is equal to 5 hr.
- Evening free time—Sunday through Thursday, this free time decreases by 1 hr.
- Number of working days in the week—reduced to 5 days.
- Being at work on a given day takes a value of zero on Friday.

Table 5 gives the prediction for the base situation and the effects of the hypothetical policy on weekly shopping behavior according to both approaches. From the table it can be seen that in the observed base situation Thursday is the major shopping day; on Friday and Tuesday there is a tendency to refrain from shopping especially during the afternoon period. On Sunday and Wednesday the shopping pattern is similar; Monday displays a slight increase in shopping, mainly during the afternoon.

The average-day model fails to reproduce the base situation because it predicts an almost identical shopping pattern for the first 5 days of the week. On the other hand, the base situation prediction according to the day-of-the-week models is quite close to observed reality. These results suggest that, when applying a model to predict changes in base behavior that are due to exogenous changes implemented differentially by day of the week, the day-of-the-week model may be expected to be more accurate.

The data in Table 5 also indicate that the average-day model predicts that the major change Sunday through Thursday is a 30 percent reduction in shopping in the afternoon. Of those who stopped shopping in the afternoon, 25 percent will switch to shopping in the morning on that day. As for Friday, the model predicts only a 13 percent increase in the participation rate. Overall, the average-day model predicts a 9 percent weekly reduction in shopping due to the shortened workweek.

The day-of-the-week model predicts a 27 percent reduction in afternoon shopping Sunday through Thursday; only 5 percent of these people will switch to morning participation. On Friday, the model predicts an increase of 85 percent in the participation rate, which is 6.5 times more than the increase predicted by the average-day model. Overall, the day-of-the-week models predict a weekly reduction of only 5 percent in shopping, which is almost half the reduction predicted by the average-day approach.

Intuitively, expectations favor the predictions produced by the daily models. That is, a dramatic increase in shopping on Friday and a small overall change in the level of total shopping during the week are expected.

CONCLUSIONS

The hypothesis that the utility an individual derives from his daily shopping pattern is not constant during the week but depends on the specific day of the week and that the utility function therefore cannot be approximated by an average utility function is examined. This hypothesis was tested by developing models of daily shopping patterns for each day of the week and comparing them with a model based on average utility function. The main findings of the empirical work are listed next.

1. The estimation results support the distinction suggested between the decision to shop and the scheduling choice for shopping. The various attributes used in the models were found to have different effects on participation and scheduling decisions.
2. The models exhibit behavior that favors the assumption that the utility function of the shopping pattern does not have a constant value but varies by day of the week.
3. The changes in the utility function are similar to the changes in the temporal constraints set, but these changes are not fully compatible. For example, on Wednesday and Thursday an individ-

TABLE 5 EFFECTS OF SHORTENING THE WORKWEEK ON SHOPPING BEHAVIOR OF 275 INDIVIDUALS WHO WORK 6 DAYS A WEEK

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday
Base situation						
No participation	177	167	189	172	159	197
Morning participation	25	19	57	24	24	59
Afternoon participation	69	82	25	76	90	17
Base prediction, day-of-the-week models						
No participation	179	168	188	172	161	196
Morning participation	27	17	60	19	13	57
Afternoon participation	65	83	23	81	99	20
Policy effect, day-of-the-week models						
No participation	196	186	195	191	197	130
Morning participation	28	19	59	17	14	124
Afternoon participation	47	63	17	65	62	19
Base prediction, average-day model						
No participation	192	190	191	192	193	182
Morning participation	23	22	25	24	31	27
Afternoon participation	56	56	55	56	49	64
Policy effect, average-day model						
No participation	203	202	203	204	205	170
Morning participation	27	26	28	27	34	83
Afternoon participation	41	41	40	41	34	20

ual may be exposed to the same set of temporal constraints and still may exhibit different behavior.

4. Average-day models based on average utility are biased when applied in anayzing a specific day of the week. Thus, when a policy that influences the activity pattern of specific days has to be evaluated, the use of day-of-the-week models is suggested. The results of the policy analysis performed indicated that there are large differences among the effects predicted by each approach.

In conclusion, the empirical results show that the daily models can represent individual behavior better and thus suggest that day-of-the-week models should be used in activity and travel pattern analysis, especially when policies that affect activity patterns during different days of the week are to be evaluated. The policy analysis results can be highly influenced by the modeling approach used. It is proposed to develop the daily model further and to study activities other than shopping, which may have a different temporal cycle. Also, the daily activity pattern can include several activities; hence daily interaction between activities can be analyzed.

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REFERENCES

1. W. Brog and E. Erl. "Interactive Measurement Methods: Theoretical Bases and Practical Applications." In *Transportation Research Record 765*, TRB, National Research Council, Washington, D.C., 1980, pp. 1–6.
2. S. Hanson and J. O. Huff. "Assessing Day-to-Day Variability in Complex Travel Patterns." In *Transportation Research Record 891*, TRB, National Research Council, Washington, D.C., 1982, pp. 18–24.
3. P. B. Goodwin. "The Usefulness of Travel Budgets." Presented at Conference on Personal Travel Budgets, Leeds, England, 1979.
4. R. Herz. "Stability, Variability and Flexibility in Everyday Behavior." In *Recent Advances in Travel Demand Analysis* (S. Carpenter and P. Jones, eds.), Gower, London, England, 1983.
5. J. N. Prashker and M. Hirsh. *Preparation of Data Base for Weekly Activity Patterns*. Publication 83–24. Transportation Research Institute, Technion-Israel Institute of Technology, Haifa, 1983.
6. J. J. Havens. "New Approaches to Understanding Travel Behavior: Role, Life-Style, and Adaption." In *New Horizons in Travel-Behavior Research* (P. R. Stopher, A. H. Meyburg, and W. Grog, eds.), Lexington Books, Toronto, Ontario, Canada, 1981.
7. C. Heidmann. "Spatial-Behavior Studies: Concepts and Contexts." In *New Horizons in Travel-Behavior Research* (P. R. Stopher, A. H. Meyburg, and W. Brog, eds.), Lexington Books, Toronto, Ontario, Canada, 1981.
8. M. Hirsh. *The Effect of Temporal Constraints on Household Travel Behavior*. M.S. thesis. Technion-Israel Institute of Technology, Haifa, 1979.
9. E. I. Pas and F. S. Koppelman. "Analysis of Multiday Travel-Activity Patterns." Presented at 65th Annual Meeting of the Transportation Research Board, Washington, D.C., 1985.
10. M. Hirsh, J. N. Prashker, and M. Ben-Akiva. Dynamic Models of Weekly Activity Pattern. *Transportation Science* (forthcoming).
11. M. Hirsh. *A Model of Urban Weekly Activity Pattern*. Ph.D. dissertation. Technion-Israel Institute of Technology, Haifa, 1984.

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Intercity Passenger Decision Making: Conceptual Structure and Data Implications

FRANK S. KOPPELMAN AND MOSHE HIRSH

Understanding intercity passenger travel behavior is important to the analysis of policies that affect intercity travel. Most studies of intercity travel behavior are based on analysis of aggregate data and lack a behavioral basis. The models developed in these studies are biased or insensitive to the effect of important policy measures, or both. A conceptual structure of the intercity passenger decision process is presented. In this behavioral framework, the first stage is to link the intercity travel decision to the individual's general process of decision making in the context of his life style and activities. In the second stage, the intercity travel decision process is grouped into four interrelated decision categories: trip generation, destination choice, mode choice, and "at-destination" decisions. Each of these categories has several dimensions, some of which have been studied in the past but not in a comprehensive framework. The conceptualization of the decision structure leads to the identification of the structure of the travel demand models needed to represent this behavior and the variables to be included in the models. The data requirements to support the proposed behavioral framework are discussed, and some methodological issues are addressed. It is concluded that the adoption of a disaggregate approach to intercity travel analysis offers substantial potential for development of improved intercity travel analysis and forecasting capabilities.

The ability to analyze intercity travel demand relationships and forecast future intercity travel is necessary to assist public agencies and private carriers in making intercity transportation service decisions. The range of public and private intercity transportation decisions that will be addressed in the future is broad, ranging from multiregional policy issues such as investment in high-speed technologies to specific improvement strategies such as adding stops to an existing rail service. The quality of these decisions depends on the quality of intercity travel analyses including the accuracy of the predicted demand and the correct identification of factors that affect the level of intercity travel demand and its distribution among the available modes. The analysis of intercity travel demand and its distribution should take account of changes in the socioeconomic and demographic environment as well as changes in intercity travel service.

A related issue is the potential impact of changes in intercity travel service on the characteristics of the metropolitan areas served. Strong positive relationships between intercity level of service and socioeconomic activity (*1*) suggest that there is a positive impact of service improvements on the activity level of metropolitan areas. This relationship is a general extension of the historical growth of cities located near waterways and rail and air hubs.

During the last two decades, substantial work has been undertaken in the development of intercity travel demand models. Both aggregate and disaggregate approaches have been used. The common denominator of all of these efforts is the absence of a behavioral framework for intercity travel analysis. That is, these efforts emphasized the estimation of statistical relationships in the available data and attempted to interpret these relationships instead of developing an understanding of the underlying behavior that determined these relationships. An overall review of these studies is given by Koppelman et al. (*2*). The main conclusions of this review are discussed here.

Initial emphasis was on development of aggregate models mostly in conjunction with the Northeast Corridor project. Several different classes of aggregate models were developed. These include direct origin-destination volume models for one and for all modes, modal share models, sequential models of total intercity volume and mode share, and models of interregional and regional demand. Although no behavioral basis supported the development of these aggregate models, they were subjected to macroeconomic reasonableness criteria and provided some insight into intercity travel behavior. The following points summarize the primary contribution of the aggregate models.

- Relevant variables: City-pair activity and attraction variables (usually population, employment, and average income) and city-pair level-of-service (travel time, cost, and frequency) were found to be statistically related to travel volume.
- Market segmentation: Segmentation by trip purpose (business and nonbusiness) and trip distance were found to be important.
- Induced demand: Trip generation and destination effects were determined to be equally important to corridor mode share in the analysis of intercity travel.
- Modal competition: Adequate forecasts of single mode volume must take account of travel service on competing modes.

Despite these contributions of aggregate intercity analysis, there are a number of issues or problems that have not been resolved. These include

- Lack of behavioral basis: The incomplete structure and specification of the aggregate models is due in part to the lack of an underlying behavioral structure.
- Unclear definition of intercity travel: There is some ambiguity about the definition of intercity travel, especially in intensely developed corridors where metropolitan regions have become contiguous.
- Deficiencies of aggregate estimation methods: Data aggregation leads to estimation bias and multicollinearity among variables; these, in turn, undermine forecast accuracy and model transferability.

Disaggregate analysis of intercity travel has been limited. These efforts, with one exception, considered only the choice of travel mode. The primary advantage of disaggregate modeling of intercity or other travel behavior results from performing the analysis at the level of the behavioral unit or decision maker: the individual, household, or firm. Analysis at this level provides a basis for

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formulating and testing hypotheses about the travel decision-making process. Thus disaggregate analysis provides a basis for improving understanding of intercity travel behavior, developing behaviorally consistent models of intercity travel behavior, and forecasting future demand with greater accuracy.

Disaggregate analyses undertaken to date have been limited by the availability of data but have, nonetheless, provided useful insights into the travel decision-making process. The single multidimensional analysis undertaken (S.A. Morrison and C. Winston, 1983) illustrates the potential of going beyond mode choice to consideration of generation, destination, and related choices. Further development of these models requires the development of a general conceptual framework, formulation of a consistently structured model system, and collection of suitable data.

CONCEPTUAL STRUCTURE OF THE INTERCITY PASSENGER DECISION-MAKING PROCESS

Introduction

A key element in the deficiencies of the existing approaches is the lack of a behavioral basis for the various models. This is an inevitable result in the development of aggregate models because the analysis is done at the level of zones, cities, or regions, whereas the behavioral unit is the individual or the household. The disaggregate models have the potential to be formulated consistently with the underlying behavioral structure. If they are not, these models also will reflect only empirical relationships with limited usefulness.

The importance of developing a behavioral framework for intercity travel is grounded in the following points:

- Identifying the relevant variables: An understanding of relevant factors and the way they affect intercity travel behavior is necessary to identify the appropriate variables and to include these factors in the models in an appropriate manner.
- Identifying the model structure: Intercity travel decisions include a number of interrelated elements that may have a hierarchical or simultaneous structure, or both. Also, intercity travel decisions may be interrelated with other decisions, though they are not pure intercity travel decisions. The behavioral framework can identify these travel and related decisions and, thereby, guide the formulation of the model system in a way that represents the underlying behavioral process and takes into account the relevant effects.
- Developing appropriate data sets: Data collection is complementary to the theoretical development. Its aim is to test the theoretical hypotheses formulated as part of the behavioral conceptualization. Because of the lack of an appropriate behavioral framework for intercity travel, travel surveys conducted in the past did not collect all of the relevant data that might be needed to test some of the more sophisticated hypotheses related to intercity travel behavior. Developing a comprehensive behavioral framework provides criteria for collecting the data needed for intercity travel analysis.
- Policy-sensitive models: If appropriate variables and a behaviorally based structure are used, the resultant models can be sensitive to many kinds of policies that directly or indirectly affect intercity travel demand. Further, not only will the models be sensitive to such policies but their predictions will be more accurate as a result of the improved representation of reality.

The balance of this section is devoted to development of a preliminary behavioral framework that can be used in the analysis of intercity travel demand.

Intercity Travel Decision Within the General Decision-Making Process

An individual's general decision-making process for activities and travel is shown in Figure 1. The inputs to this process are the characteristics of the individual and his household. These characteristics are related to the individual's needs and ability to participate in various activities. To this category belong attributes like the individual's age and education and the household's stage in the life cycle. It is assumed that the household structure is given, and decisions about household formation are not considered within the proposed framework.

Given these attributes, long-range decisions about place of residence (type, city, location), occupational level and work place, and level of automobile ownership are made. These decisions were described by Lerman and Ben-Akiva (*3*) as household mobility decisions. In the intercity context, these decisions define the environmental attributes of the individual, and, together with personal and household characteristics, they define the preferences of the individual and the system of influence acting on him.

The long-range decisions serve as the basic input to the next set of decisions that are referred to as life-style decisions. There are many definitions of life style, but, in this context, life style is represented by the various activity patterns of the individual. These patterns usually exhibit regularities that correspond to daily, weekly, and seasonal routines. The term "activity pattern" refers to the types of activities performed by an individual and their order and duration.

Individual travel decisions are derived from the various activity patterns. For the purpose of this paper, travel patterns are divided into urban and intercity travel patterns. As will be shown later, these two patterns are distinct. In some contexts, intercity travel may be further broken down into domestic and international travel.

It follows from this brief description that intercity travel analysis should take account of individual and household characteristics, residential and work location, automobile ownership, and developmental and service characteristics of an individual. Further, when analyzing intercity travel, special attention should be given to the potential for substituting urban travel for intercity travel. At a minimum, this means that the alternative of not making an intercity trip should be present in the analyzed individual choice set. As can be seen from Figure 1, many factors affect intercity travel decisions. Neglecting them may lead to misrepresentation of an individual's decision-making process. A critical modeling issue is the identification of those elements that can be excluded from the analysis of intercity travel without undermining the interpretational and predictive usefulness of the resultant model system.

Dimensions of Intercity Travel Decisions

The intercity travel decision has many dimensions, which means that more than one decision precedes the execution of an intercity trip. Figure 2 shows the dimensions associated with the intercity decision-making process. These dimensions are categorized under the traditional classification of the travel decision process: trip generation, distribution, and mode choice. To these are added another class, "decisions at the destination."

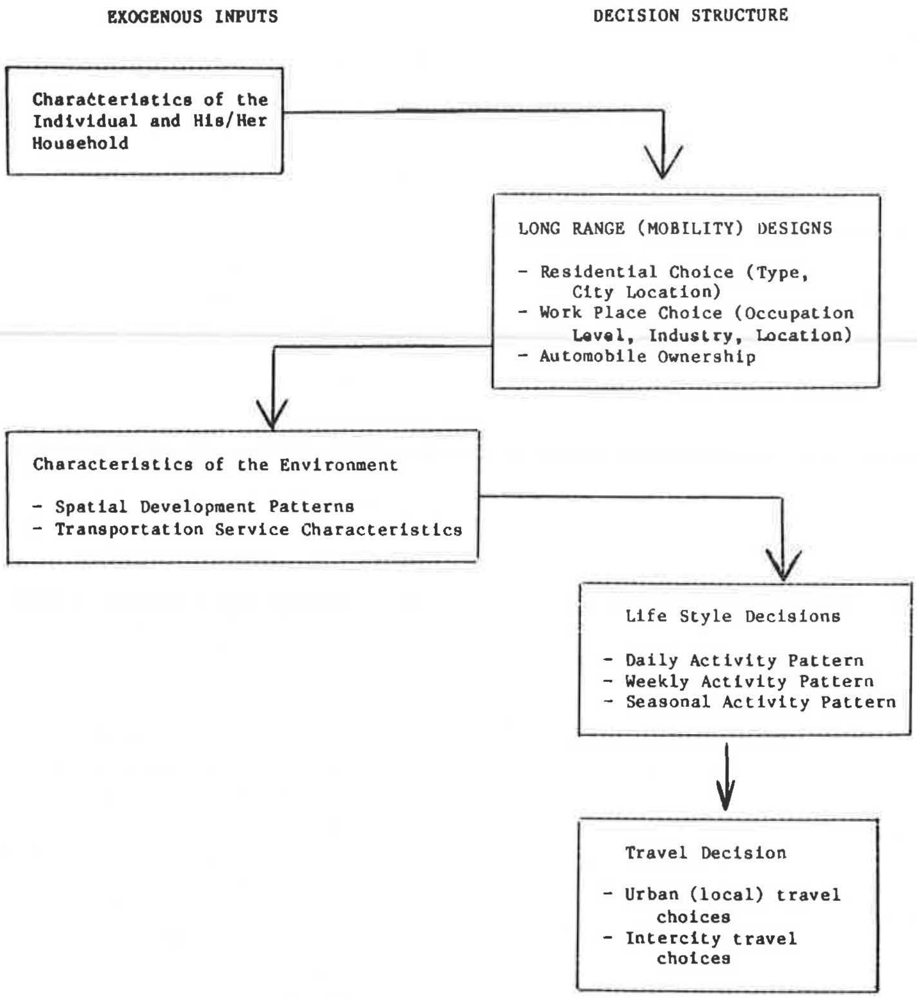

FIGURE 1 Intercity travel decisions within the general decision-making process.

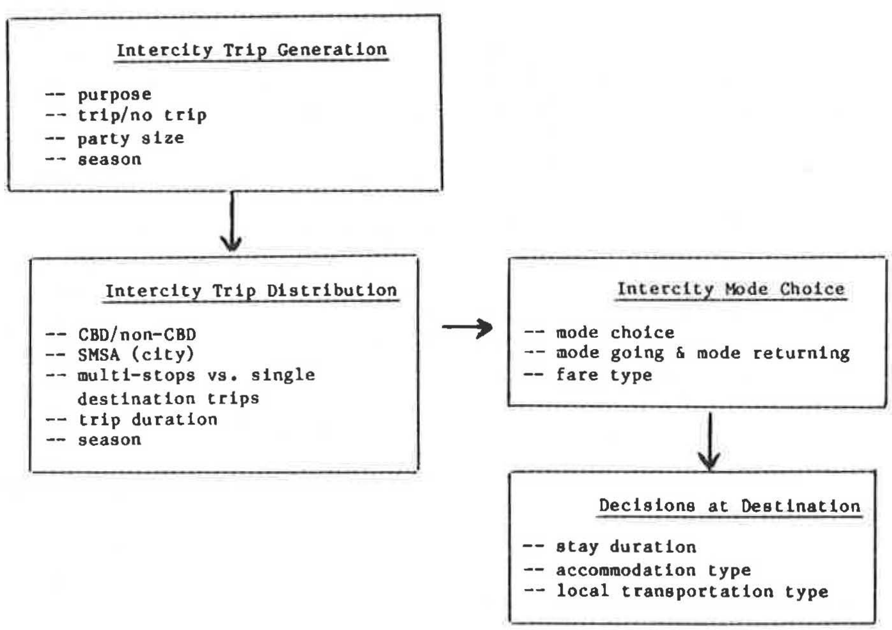

FIGURE 2 Dimensions associated with intercity travel decision making.

The first step in the suggested decision-making process is the trip generation phase. Here, the individual first decides whether or not to make an intercity trip. Given that a positive decision to undertake an intercity trip is made, several related decisions have to be made. Traditionally, only the trip purpose dimension is considered at this stage and, usually, the models deal with trip purpose by means of market segmentation (*4, 5*). Such segmentation implies that trips are generated explicitly for different purposes, which appears to be appropriate in many contexts; however, it ignores the potential of combining business and recreational travel. Further, there are other dimensions that are important at this stage. Party size has been identified and used in two studies as an explanatory variable for mode choice [Direnzo and Rossi (*6*) and Morrison and Winston, 1983]. However, neither of these studies attempts to estimate size. Another determinant that appears to be relevant is the time-of-the-year dimension of the intercity trip. Travel during the winter may be different from travel during the summer. Significant seasonal variations in trip generation have been identified in some data sets (*7*).

The second stage of the decision-making process is trip distribution or destination choice. Most models do not address this stage separately but combine it with the trip generation or the mode choice step, or both, to form a direct demand model (*8, 9*). Few studies, however, treat the destination choice separately or explicitly consider competition among destinations. Some studies in this category develop trip generation or mode choice models for specific destination segments, such as central business district (CBD) versus non-CBD destinations (*6*); stratify models according to distance (*10*); or develop models for specific corridors (*11, 12*). Only one disaggregate study (Morrison and Winston, 1983) actually modeled the destination choice for recreational travel using a choice set that was composed from several specific metropolitan areas.

In all of these studies, however, only one destination is considered for the intercity trip. This restriction limits the usefulness of the analysis because intercity trips may have multiple stops. Another dimension of destination choice is trip duration. Because this dimension may be an important input to the mode choice stage, it should be studied explicitly. Further, it is reasonable to hypothesize that trip distribution has a seasonal component.

The third stage in the decision-making process, mode choice, is the most extensively and, in many cases, the only aspect analyzed. All of the mode choice models developed to date considered only the origin-to-destination mode for the trip and implicitly assumed that the same mode is used for the return trip. The models are formed as either binary choice or multinominal choice models. In the latter case, a violation of the independence of irrelevant attributes (IIA) assumption may exist because the automobile mode may be treated differently than the common carrier modes. Future research should address this problem. Another important issue in the mode choice stage is the distinction between the mode going and the mode coming back. In this respect, automobile travelers are usually captive to the chosen mode and common carrier travelers have more freedom.

An important aspect of mode choice, especially for policy analysis purposes, is the choice of fare and service type. Intercity carriers offer a range of fare types associated with the level of service and the amenities offered. The existence of several fare classes is especially true in the airline industry, which may offer many different fare classes for the same flight (e.g., first class, business class, coach fare, excursion fare, and one or more restricted discount fares). From the point of view of the carrier, the number of seats to be allocated to each class (or the introduction of a new class) is one of the most important marketing decisions because changes in travel time between city pairs are limited and changes in service frequency incur substantial cost differences. Similar service class options may be important in intercity rail and bus marketing programs. Because of the potential importance of the service class decision, an individual's choice of fare type should be addressed explicitly in future analyses.

The three stages discussed so far form the conventional decision-making process associated with travel behavior. However, for a comprehensive analysis, intercity travel choices should not be separate from local activity pattern at the destination. The precise location of the intercity destination and the need for mobility at the destination may influence intercity travel choices. Of all the related decisions made at the destination, three dimensions appear to be most important. These are duration of stay at the destination, arrangements for accommodation, and transportation available at the destination. A recent study (Morrison and Winston, 1983) found statistically significant relationships between the decision to rent a car at the destination and the mode chosen for nonbusiness intercity trips.

A preliminary proposal for a behavioral framework of intercity travel has been presented. Developing a fully comprehensive framework requires the development of a system of corresponding models to test the various hypothesis implied in this structure.

DATA IMPLICATIONS

Requirements for the Data Set

An appropriate data set is needed to validate and refine the model system described previously. A data set should satisfy the following requirements to accomplish this objective.

- Fully disaggregate data: The data have to be gathered at the individual or the household level. This task is accomplished by interviews at the residence or work place. However, the interviews may need to be supplemented from other sources especially for the data that describe the level of service supplied by the nonchosen modes. Supplementing the data by using average city-to-city values for the missing information is equivalent to an error in measurement that may substantially undermine the effectiveness of the model.
- Compatibility with behavioral framework: Testing and supporting the behavioral framework can be done only with data that are relevant to the conceptualized decision-making process. This means that the candidate data set should include the following items: (*a*) personal and familial characteristics of the individual; (*b*) actual behavior in intercity travel over a substantial period of time; (*c*) full description of all of the intercity trips undertaken during this period (i.e., purpose, party size, time of the year); (*d*) relevant information about the destinations visited (i.e., city, specific areas visited, number of stops, trip duration); (*e*) attributes of the modes chosen for the trip as well as the corresponding attributes of the nonchosen modes; for any mode that offers several alternatives for service, all of the alternatives should be included in the data; and (*f*) description of the local activity pattern at the destination (i.e., length of stay, accommodations, and transportation arrangements).
- Compatibility of definitions of data items from various sources: Usually, a complete intercity travel data base contains information from various sources. Definition of city bounds, intercity distances, and level of service for the various modes should be

consistent. Attention should be given to eliminating ambiguous and confusing definitions from the data.

In light of these criteria, none of the existing data sets include all of the desired information. Most of the available data sets are in aggregate form. So-called disaggregate studies have used the 1977 National Personal Transportation Study (NPTS) (*13*) or the 1977 National Travel Survey (NTS) (*14*). These provide disaggregate data on individual trips of 75 or 100 mi and longer during a recall period of 14 days or a full year for the NPTS and the NTS, respectively. There are three major issues that limit the usefulness of these data sets:

- The data sets do not include accurate information on the place of residence of the respondents (this is to satisfy privacy restrictions). Thus access and egress time and cost for the trips cannot be constructed and used in the models.
- The specific origin and destination cities are not identified in some cases because of the use of standard metropolitan statistical area (SMSA) codes for both the origin and the destination. Hence, if one of the trip ends is not within an SMSA, the location of that trip end is not known. Also, the SMSA usually covers a large geographical area.
- The fare class used for common carrier trips is not given. Because many fare classes may exist for the same trip, this eliminates the ability to model fare class choice and limits the usefulness of the mode choice models because of error in travel cost variables.

Nonetheless, the 1977 NTS data set was used in a disaggregate study (Morrison and Winston, 1983) and revealed the potential usefulness of the disaggregate approach in exploring further aspects of intercity behavior; specifically, the development of interrelated multidimensional choice models.

Issues in Developing a New Data Base for Intercity Travel

In preparing a new intercity travel data base, several methodological issues should be addressed:

- Clear and unique definitions of relevant terms: The complexity of the intercity travel phenomenon necessitates the establishment of a well-defined terminology before data are collected. Special attention should be given to the definition of intercity travel especially in intensely developed corridors.
- Population frame and sample design: Because no disaggregate intercity travel data set was collected in the past to support a comprehensive study, basic issues such as population frame (i.e., region size), sample size, and sampling procedure have to be addressed. Also, attention should be given to the data collection strategy. Because time of the year may affect intercity travel, it would be desirable to collect data during the entire year. Also, because bias may result from omitting households that are absent for a long period during the data collection stage, a careful protocol for follow-up contact should be developed.
- Design of questionnaire: The data needed from the interviewee are more complex and extensive than the data collected in most urban travel surveys and the individual is required to supply information for an extended time period. There is a need to establish procedures that minimize dependence on long-term recall.
- Combining various data sources into one data base: In preparing an intercity travel data base, information needs to be extracted from several sources, especially for the level of service supplied by the nonchosen modes. Combining data should be done carefully to ensure uniqueness of definitions and compatability among data items. Also, attention should be given to the possible mixture of reported level of service with measured level of service data.
- Exploiting existing data sets: Because of the complexity of the intercity travel phenomenon, collecting a new data base can be a costly project. It may be more cost-effective to use various existing data sets or to coordinate this effort with other data collections.
- Updating the data base: When an intercity travel data base has been established, methods should be developed to update the information. Changes that occur in the general environment and in the transportation system need to be continuously incorporated into the data base so that it is not out of date when it is needed.

SUMMARY

A conceptual structure of the intercity passenger decision-making process has been presented and some of the implications for data base needs and data preparation have been noted. Accurate, policy-sensitive analysis is especially important for purposes of policy evaluation. Undertaking such analysis at the aggregate level is ineffective for policy evaluation; therefore a disaggregate approach is recommended. A key element in analysis of intercity travel is the development of an appropriate behavioral framework. Such a framework is needed for identifying the relevant variables and the correct model structure and is important to the development of a suitable intercity travel data set.

The first stage in the suggested behavioral framework is to link the intercity travel decision to the individual's general decision-making process. These linkages show that intercity travel can be interchanged with other decisions, so intercity models should include the alternative of no intercity trip in the individual's choice set.

The suggested decision-making process is categorized under four successive but interrelated decisions: trip generation, distribution, mode choice, and decisions at destination. Each of these categories has several dimensions, some of which have been studied in the past.

The establishment of a firm and detailed behavioral framework requires an appropriate data set. The data set should be fully disaggregate and contain information that is relevant to testing the underlying behavioral assumptions. In preparing the data set, several methodological issues have to be addressed. These include population frame, sample design, questionnaire design, combining various data sources, exploiting existing data sets, and updating the data.

Adoption of a disaggregate approach to intercity travel analysis and use of a suitable data base offer substantial potential for development of an improved intercity travel analysis and forecasting capability.

REFERENCES

1. A. H. Meyburg. "An Analysis of the Relationship Between Intercity Passenger Transportation and the Socio-Economic Characteristics of Metropolitan Areas." *Proc., Transportation Research Forum*, 1972.
2. F. S. Koppelman, G. K. Kuah, and M. Hirsh. *Review of Intercity Passenger Travel Demand Modelling: Mid-60's to the Mid-80's*. The

Transportation Center and Department of Civil Engineering, Northwestern University, Evanston, Ill. 1984.
3. S. R. Lerman and M. E. Ben-Akiva. "Disaggregate Behavioral Model of Automobile Ownership." In *Transportation Research Record 569*, TRB, National Research Council, Washington, D.C., 1976, pp. 34–55.
4. C. A. Lave, S. Mehring, and R. Kuzmyak. "Price Elasticites of Intercity Passenger Travel." *Proc., Transportation Research Forum*, 1977.
5. G. S. Cohen, N. S. Erlbaum, and D. T. Hartgen. "Intercity Rail Travel Models." In *Transportation Research Record 673*, TRB, National Research Council, Washington, D.C., 1978, pp. 21–25.
6. S. F. DiRenzo and L. P. Rossi. "Diversion Model for Estimating High-Speed Rail Use." In *Highway Research Record 369*, HRB, National Research Council, Washington, D.C., 1971, pp. 15–25.
7. A. Stachurski and R. Rice. "Development of Direct Intercity Rail Passenger Demand Models." *Proc., World Conference on Transportation Research*, London, England, April 1980.
8. G. Kraft. *Demand for Intercity Passenger Travel in the Washington-Boston Corridor*. NTIS: PB166–884. Systems Analysis and Research Corporation, Boston, Mass., 1963.
9. R. E. Quandt and W. J. Baumol. The Abstract Mode Model: Theory and Measurement. *Journal of Regional Science*, Vol. 6, No. 2, 1966, pp. 13–26.
10. S. E. Eriksen. *Demand Model for U.S. Domestic Air Passenger Markets*. Flight Transportation Report R78–2. Massachusetts Institute of Technology, Cambridge, June 1978.
11. P. L. Watson. "Comparison of the Model Structure and Predictive Power of Aggregate and Disaggregate Models of Intercity Mode Choice." In *Transportation Research Record 527*, TRB, National Research Council, Washington, D.C., 1974, pp. 59–65.
12. G. R. Leake and J. R. Underwood. Comparison of Intercity Bi-Modal Split Models. *Transportation Planning and Technology*, Vol. 5, 1978, pp. 55–69.
13. *1977 National Personal Transportation Study, User Guide for Public Use Tapes*. FHWA, U.S. Department of Transportation, 1980.
14. *National Travel Survey—Travel During 1977*. Bureau of the Census, U.S. Department of Commerce, Oct. 1979.

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Constraints on Individual Travel Behavior in a Brazilian City

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In this paper the statistical and predictive performance of two disaggregate choice models that incorporate probabilistic choice set formation are compared with a standard logit specification. The empirical work is conducted with work mode choice data from a Brazilian city. For the type of travel demand analyzed it is found that, although statistically inferior to the probabilistic choice set specifications, the standard logit specification, allied with market segmentation, is a robust formulation in both statistical and predictive terms. Recommendations for future research work in probabilistic choice set modeling are presented.

The principal issue addressed by this paper is the appropriateness of choice theory, as it is now interpreted, for modeling travel demand. In a highly constrained environment, such as can be found in low-income areas, observed choice may well be the result of the elimination of alternatives through active constraints, as opposed to the exercise of a choice prerogative by the decision maker.

The effect of constraints on travel behavior is particularly important for analyses in developing nations. Swait et al. *(1)* present an extensive discussion of a disaggregate travel demand model system for a medium-sized Brazilian city. Because of its unique nature, many substantive conceptual and modeling issues have arisen during the course of the study. These issues highlight fundamental differences between developed and developing countries in terms of travel demand. These practical experiences and conceptual concerns have led to the investigation and formulation of a number of probabilistic choice set formation models and to empirical testing of these to investigate their performance with respect to choice models with fixed choice sets.

The overall methodology and the alternative models that incorporate probabilistic choice sets are described in Ben-Akiva and Swait *(2)* and in Swait and Ben-Akiva *(3)*. In this paper two of these models are implemented with data for work mode choice from Maceió, Brazil, and their statistical fit and forecasts are compared with those of a standard logit model.

HYBRID APPROACH TO MODELING CHOICE SET GENERATION

The approach used in this work is based on the following two-stage choice process: first, constraints (of a personal, household, and social nature) act on the individual to define his choice set; second, the individual exercises choice according to some decision rule.

From the perspective of an analyst who normally does not know either the specific alternatives that constitute an individual's choice set or the exact decision rule used to make a choice, the two-step choice paradigm leads to the following probability of observing alternative j being chosen by individual n *(4)*:

$$P_n(j) = \sum_{C \in G_n} P_n(j|C)\, P_n(C) \tag{1}$$

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where

M = the universal choice set, made up of all possible alternatives available for the choice context and population in question;
M_n = the set of all deterministically feasible alternatives for individual n $(M_n \subseteq M)$;
G_n = the set of all nonempty subsets of M_n; and
C = an element of G_n $(C \subseteq M_n)$.

Expression 1 reflects a three-part model of the choice process:

1. A probabilistic choice model, $P_n(j|C)$, conditioned on the choice set being $C \in G_n$, which by definition yields choice probabilities of zero for $j \notin C$;
2. A deterministic choice set generation model that determines the subset M_n from the set M; and
3. A probabilistic choice set generation model, $P_n(C)$, expressing the probability that set $C \subseteq M_n$ is the individual's actual choice set.

This reflects the assumption that the analyst may be willing to impose certain constraints deterministically because of a high level of assurance about their effect (e.g., no automobile driver mode for individuals without a driver's license) but unwilling to do the same for other constraints (e.g., acceptable walk access distances at the origin and destination of a specific trip).

A high degree of computational complexity is implied by Expression 1. If $|C|$ denotes the number of elements in set C, then $|G_n|$ is equal to $(2^{|M_n|} - 1)$, of which $(2^{|M_n|-1})$ choice sets actually contain any given alternative $j \in M_n$. To illustrate how the number of possible choice sets can quickly become overwhelming, if M_n has 3 alternatives, then 4 terms must be summed; with 10 alternatives, the number of possibilities has increased to 512. These sizes are applicable for model estimation; for prediction, when choice probabilities must be evaluated for all the alternatives in M_n, there are $(2^{|M_n|} - 1)$ possible choice sets (e.g., if $|M_n| = 3$ then $|G_n| = 7$).

Most choice contexts of interest are, unfortunately, characterized by many, rather than few, alternatives. A possible approach to reducing the dimensionality of the choice set generation problem is to place a priori restrictions of the members of G_n. That is, modeling the choice situation at hand requires only a subset of the $(2^{|M_n|} - 1)$ possible sets. One useful restriction is the captivity model, in which an individual is assumed either to be captive to a single alternative or to be free to choose from among the full set of deterministically available alternatives. Assuming that the choice model has the logit form, the following logit captivity model is obtained:

$$P_n(i) = [\delta_i/(1 + \sum_{j \in M_n} \delta_j)] + [1/(1 + \sum_{j \in M_n} \delta_j)]$$

$$\exp(V_{in})/\sum_{l \in M_n} \exp(V_{ln}) \qquad (2)$$

where V_{in} is the systematic utility of the ith alternative, and δ is a vector of nonnegative parameters that represents the odds of the individual being captive to each specific alternative. The first term on the right side of Expression 2 represents the probability that the individual is captive to alternative i, in which case the probability of i being chosen is obviously one. The second term has two parts: the one involving the δ vector represents the probability that the choice is to be from the full choice set M_n, and the other is a logit model of the probability of choosing i given that the choice set is M_n. The reader is referred to Ben-Akiva and Swait *(2)* for a more detailed development of this model.

This logit captivity model was derived by McFadden (unpublished memorandum of September 30, 1976), Ben-Akiva *(5)*, and Gaudry and Dagenais *(6)*, the first two motivated by the probabilistic captivity concept and the last, who refer to this model as "dogit," by the desire to circumvent the independence of irrelevant alternatives (IIA) property of the logit model.

A probabilistic choice set formation model with no a priori restrictions on G_n will also be used here. One specific model, called the independent availability logit model, assumes that the probability of availability of an alternative is independent of the availability or lack thereof of any other alternative. This strong assumption is necessary to achieve a manageable model specification. The mathematical formulation of this model is

$$P_n(C) = \prod_{i \in C} \gamma_i \prod_{j \in M_n - C} (1 - \gamma_j)/[1 - \prod_{l \in M_n} (1 - \gamma_l)],$$

$$C \in G_n \qquad (3)$$

$$P_n(j|C) = \exp(V_{jn})/\sum_{i \in C} \exp(V_{in}), \quad j \in C \qquad (4)$$

where γ_i is the probability that alternative $i \in M_n$ is available and other quantities are as previously defined. The notation $M_n - C$ denotes the set of the alternatives in M_n less the alternatives in C. Expressions 3 and 4 can be substituted into Expression 1 to obtain the unconditional probability of choice of an alternative.

In Expression 3 the first term in the numerator represents the probability of availability of all of the alternatives in C, and the second the probability of unavailability of all the alternatives in M_n not in C. The denominator is a normalization factor to exclude the event of all alternatives being unavailable.

In the two models, the representation of constraints is done in a simple manner, either by the captivity restriction on possible choice sets or by the simplifying assumption of independent availability. In addition, in both specifications the aggregate impact of these constraints is represented by a single parameter per alternative (i.e., δ_i and γ_i, $i \in M_n$, in the captivity and independent availability models, respectively). Swait and Ben-Akiva *(3)* present an example of a logit captivity model in which this latter restriction is relaxed.

The calibration results of standard logit, logit captivity, and independent availability logit models of work mode choice for Maceió, Brazil, are presented in the following section. The various models are compared on the basis of statistical performance. Following this, the three models are used to produce forecasts in a variety of policy scenarios. These forecasts are compared and their implications are discussed.

ESTIMATION RESULTS

Choice Context

The city of Maceió and its travel patterns have been extensively described in Swait et al. *(1)* and in Geltner and Barros *(7)*. The particular choice dimension to be investigated is that of home-based work mode choice for full-time workers. Because of the widespread habit of returning home for lunch and important policy implications of this type of behavior, the unit of observation is the modal choice pattern for a working day. An investigation of the observed modal choice patterns of Maceió workers, captured in a 1977 household survey, reveals that fewer than 5 percent of the workers chose travel patterns that involved more than one mode. Hence, the universe of alternatives (i.e., the set M) is reduced (for modeling purposes) to

- Bus,
- Taxi,
- Automobile driver, and
- Automobile passenger.

Thus "modal alternative" actually refers to the use of that mode by the worker for all home-based work trips taken that day.

The following deterministic constraints were applied to the alternatives:

- The automobile driver alternative is available only to individuals from automobile-owning households who are 18 years or older (no information was available on driver's license) and
- If the one-way network travel time for the mode is greater than 2 hr, it is unavailable.

Thus bus, taxi, and automobile passenger are ubiquitous; automobile driver is limited to those eligible for a driver's license and whose households own a vehicle. The travel time limitation is a further imposition.

To provide a basis for comparison, a standard logit model is first estimated with a random sample of 1,477 workers. Next, market segmentation is used as a first attempt to account for the impact of constraints and taste variations on choice. Following that, the estimation results of the logit captivity and independent availability logit models are presented in turn.

Standard Logit Model

Table 1 gives the estimation results for the standard logit model of home-based full-time worker mode choice for the full data set and three income market segments. The 19 parameter models include time, cost, income, family size, automobile availability, and role-related variables, which, with one exception, show high levels of significance and correct signs. Though no extensive efforts were expended to obtain an improved specification, it is believed that the pooled model as it now stands represents a reasonable standard for comparison.

Inclusion of variables such as automobile availability, income, and family size in the utility functions of alternatives can be interpreted as an ad hoc model of alternative availability in much the same way that size variables are used to correct for aggregation of alternatives in logit models of destination choice *(8)*.

To maintain uniformity during model comparisons, this same specification has been used for the choice model throughout the study of Maceió; exceptions have been opened only in the case of unidentifiability.

Market segmentation is a useful technique for accounting for taste variations in a population, but it can also be used to bring out the impact of constraints on choice. The market segmentation used is based on household income; for Maceió monthly household electrical energy consumption is used as a proxy measure of income [see Swait et al. *(1)* for more discussion of this measure]. The three income groups are *(a)* less than 80 KwH/month (low), *(b)* 80 to 130 KwH/month (medium), and *(c)* greater than 130 KwH/month (high). Because Maceió is located in an economically depressed area of Brazil, it is to be expected that income should play a significant role in determining mode choice. For the three income segment logit models in Table 1 the hypothesis of parameter equality across the segments is rejected with a very high level of significance (more than 99 percent for a chi-squared statistic of 71.2, compared with a critical value of 63.7 with 40 degrees of freedom). The apparent parameter differences appear to be concentrated mainly in the socioeconomic attributes, such as income (the significance of which is quite diminished in the income segment models, which indicates that the segmentation has reduced within-group variation with respect to this variable), household size, and automobile availability. The travel impedance parameters are not very different across segments.

Although the market segmentation results are encouraging, it is impossible to attribute any part of the improvement to a better choice model specification because of accounting for taste variations, or to improved "modeling" of constraints on choice with ad hoc availability variables.

Logit Captivity Model

The logit captivity model represents a choice context in which the decision maker either is captive to one alternative or is free to choose from the full set of available alternatives. Table 2 gives the estimation results for this specification; the choice model parameters (i.e., those for the logit model) are directly comparable with the parameters in Table 1. Note that the model in Table 2 maintains the hypothesis of no captivity to the automobile driver mode for workers who have this alternative. Although this restriction appears to be plausible for the city of Maceió, it is important to realize that this restriction is not arbitrary: it is the result of the parameter being driven to zero during optimization of the log-likelihood function for the Maceió sample. This type of parameter restriction will be seen in each of the choice set models presented in this paper.

First, the standard logit and logit captivity estimated with the full sample are compared. With a chi-squared statistic of 3.8 with 3 degrees of freedom, the hypothesis, at a 90 percent significance level, that the captivity parameters are jointly zero for the pooled sample cannot be rejected. Further, the hypothesis that each parameter is individually zero also cannot be rejected at reasonable significance levels. Thus there appears to be little evidence of captivity for the sample of workers as a whole. This is not, of course, a surprising result: the radical choice set structure (i.e., captivity or complete freedom of choice) of this model is unlikely to be generally applicable to the population.

This lack of significant improvement over the fit of the logit specification and the significant improvement obtained by the income segmentation (Table 1) compared to the pooled sample led to the hypothesis that evidence of captivity could perhaps be uncovered by calibrating logit captivity models by income group.

The income segmentation results for the logit captivity model in Table 2 indeed bring to light significant captivity to the bus mode in the low-income group and to the bus and automobile passenger modes in the medium-income group. There is indicated a small degree of captivity to automobile passenger in the high-income

TABLE 1 MACEIÓ HOME-BASED WORK TOUR MODE CHOICE MODEL—LOGIT SPECIFICATION

	Estimated Parameters			
Parameters	Low Income	Medium Income	High Income	All
Alternative-specific constants				
Bus	0	0	0	0
Taxi	0.05 (0.0)	-1.30 (-0.5)	0.78 (0.7)	-1.29 (-2.5)
Automobile passenger	-3.47 (-2.0)	-3.30 (-1.8)	-2.17 (-2.3)	-2.88 (-7.5)
Automobile driver	1.14 (0.6)	0.50 (0.3)	0.12 (0.1)	0.02 (0.0)
Total travel time (min/day)	-0.008 (-1.0)	-0.014 (-2.3)	-0.011 (-1.8)	-0.012 (-3.5)
Total travel cost (Cr$ 1977/day divided by ℓn (household income, Kwh/month)	-0.245 (-2.1)	-0.318 (-3.8)	-0.342 (-2.6)	-0.296 (-5.9)
Household income (KwH/month)				
Bus	0	0	0	0
Taxi	0.001 (0.1)	-0.010 (-0.4)	0.001 (0.3)	0.005 (2.7)
Automobile passenger	0.020 (1.0)	0.016 (0.9)	0.003 (1.2)	0.007 (5.1)
Automobile driver	0.008 (0.4)	0.026 (1.5)	0.002 (0.9)	0.006 (4.8)
No. of household members				
Bus	0	0	0	0
Taxi	-0.44 (-2.5)	0.18 (1.7)	-0.32 (-2.9)	-0.11 (-2.1)
Automobile passenger	0.26 (-1.9)	-0.16 (-1.7)	-0.17 (-2.1)	-0.15 (-3.0)
Automobile driver	-0.26 (-1.1)	-0.57 (-4.1)	-0.17 (-2.2)	-0.21 (-3.9)
Automobile availability (cars/workers)				
Bus	0	0	0	0
Taxi	3.94 (2.8)	1.37 (1.4)	2.03 (3.3)	1.81 (4.3)
Automobile passenger	3.62 (2.8)	2.47 (6.2)	3.84 (8.3)	3.10 (11.3)
Automobile driver	2.04 (2.1)	1.89 (3.3)	3.92 (8.2)	2.88 (9.6)
CBD work location and lunch trip home				
Bus	0	0	0	0
Taxi	0.3 (0.3)	0.3 (0.5)	1.3 (2.4)	0.7 (2.1)
Automobile passenger and driver	-0.3 (-0.4)	-0.5 (-1.2)	0.1 (0.3)	-0.2 (-0.7)
Female worker				
Bus, taxi, automobile passenger	0	0	0	0
Automobile driver	-1.7 (-1.8)	-2.0 (-4.2)	-1.6 (-5.0)	-1.7 (-7.0)
Professional worker and lunch trip home				
Bus	0	0	0	0
Taxi	-0.5 (-0.4)	0.4 (0.5)	1.4 (2.8)	0.8 (2.3)
Automobile passenger and driver	0.9 (1.2)	0.6 (1.4)	1.5 (3.6)	1.0 (4.2)
Summary Statistics				
Log-likelihood at zero	-596.5	-532.8	-649.8	-1779.0
Log-likelihood at convergence	-129.0	-237.3	-319.0	-720.9
Rho-squared	0.7837	0.5546	0.5090	0.5948
Adjusted rho-squared[a]	0.7519	0.5190	0.4798	0.5841
Sample Description				
Choosing				
Bus	467	301	163	931
Taxi	12	18	25	55
Automobile passenger	14	39	67	120
Automobile driver	35	88	248	371
Total observations	528	446	503	1,477

Note: Asymptotic t-statistics in parentheses for the hypothesis the parameter is zero.
[a]See Expression 5 for the definition of this measure.

group, but this is not statistically significant because of the large variance of the respective captivity parameter. It is clear that the income segment captivity models are a statistically significant improvement over the pooled logit model of Table 1 and the pooled logit captivity model of Table 2.

The income segment logit captivity models are also jointly a statistically significant improvement over the income segment logit models of Table 1. The hypothesis that the captivity parameters are all jointly zero is tested by using a chi-squared statistic of 24.8, which can be compared with a critical value of 23.2 at the 99 percent significance level with a conservative 10 degrees of freedom. Therefore this hypothesis is rejected; the data indicate that in addition to the taste variations that are captured by the income segmentation in Table 1, there is a variation in the choice set structure of individuals that must be accounted for in the choice model specifications. Bear in mind, however, that the major source of improvement stems not from choice set modeling but from income segmentation.

Also note that the logit captivity models provide statistically better fit across all three income segments than do their standard logit counterparts of Table 1. It is also interesting to note some of the significant changes that have occurred in certain individual parameters of the logit model utilities.

Consider, for example, the coefficients of the travel time and cost variables. Those in the logit captivity models are uniformly larger than the corresponding parameters in Table 1. Conceptually, the removal of captives from consideration in the calibration of the choice model removes their diluting effect on its parameters; only the true choosers affect the choice model parameters. Indeed, all of the travel impedance and socioeconomic parameters grow in magnitude, some of them quite drastically (e.g., automobile availability in the low-income group).

TABLE 2 MACEIÓ HOME-BASED WORK TOUR MODE CHOICE MODEL–LOGIT CAPTIVITY SPECIFICATION

	Estimated Parameters			
	Low Income	Medium Income	High Income	Pooled
Choice Model Parameter				
Alternative-specific constants				
Bus	0	0	0	0
Taxi	2.14 (0.6)	0.37 (0.1)	1.35 (1.0)	-1.13 (-2.0)
Automobile passenger	-2.16 (-0.8)	-5.72 (-1.3)	-2.32 (-2.0)	-3.02 (-6.3)
Automobile driver	2.79 (0.7)	2.15 (0.6)	0.17 (0.2)	-0.07 (-0.2)
Total travel time (min/day)	-0.012 (-0.4)	-0.041 (-2.4)	-0.013 (-1.8)	-0.014 (-3.4)
Total travel cost (Cr$ 1977/day) divided by ℓn (household income, KwH/month)	-0.543 (-1.4)	-0.826 (-2.8)	-0.451 (-2.8)	-0.356 (-4.7)
Household income (KwH/month)				
Bus	0		0	0
Taxi	0.112 (0.9)	-0.014 (-0.4)	0.001 (0.3)	0.006 (2.7)
Automobile passenger	0.034 (1.0)	0.029 (0.7)	0.002 (0.8)	0.007 (4.2)
Automobile driver	0.023 (0.6)	0.041 (1.3)	0.001 (0.4)	0.006 (3.9)
No. of household members				
Bus	0	0	0	0
Taxi	-3.12 (-1.2)	0.24 (1.7)	-0.36 (-2.8)	-0.11 (-1.9)
Automobile passenger	-0.71 (-1.6)	-0.36 (-1.4)	-0.25 (-2.0)	-0.17 (-2.7)
Automobile driver	-0.58 (-1.1)	-1.06 (-2.9)	-0.22 (-2.2)	-0.22 (-3.6)
Automobile availability (cars/workers)				
Bus	0	0	0	0
Taxi	11.67 (1.7)	2.58 (1.7)	2.11 (1.5)	1.87 (3.1)
Automobile passenger	10.79 (2.1)	4.61 (3.1)	5.16 (5.0)	3.63 (8.1)
Automobile driver	10.43 (2.2)	2.83 (2.0)	5.57 (5.3)	3.44 (7.6)
CBD work location and lunch trip home				
Bus	0	0	0	0
Taxi	-0.2 (-0.1)	1.8 (1.8)	1.7 (2.5)	0.8 (2.2)
Automobile passenger and driver	-0.3 (-0.2)	-0.4 (-0.5)	0.2 (0.4)	-0.1 (-0.5)
Female worker				
Bus, taxi, automobile passenger	0	0	0	0
Automobile driver	-4.4 (-3.0)	-3.2 (-3.1)	-1.9 (-4.3)	-1.7 (-6.6)
Professional worker and lunch trip home				
Bus	0	0	0	0
Taxi	NI[a]	0.2 (0.2)	1.8 (2.9)	1.0 (2.4)
Automobile passenger and driver	NI	1.2 (1.5)	1.9 (2.9)	1.1 (3.8)
Captivity Parameters				
Bus	0.167 (2.1)	0.099 (2.0)	0.011 (1.1)	0.013 (1.2)
Taxi	0.016 (2.4)	0.010 (1.3)	0.007 (1.1)	0.004 (0.9)
Automobile passenger	0.007 (1.0)	0.058 (2.7)	0.044 (1.4)	0.008 (0.8)
Automobile driver	0	0	0	0
Summary Statistics				
Log-likelihood at $\beta = 0, \delta = 0$	-596.5	-532.8	-649.8	-1779.0
Log-likelihood at convergence	-124.9	-234.5	-313.5	-719.0
Rho-squared	0.7907	0.5599	0.5175	0.5958
Adjusted rho-squared	0.7571	0.5186	0.4837	0.5835

Note: Asymptotic *t*-statistics in parentheses.
[a]NI = not identifiable or not included.

These large changes have occurred in the presence of what is not a large captivity effect. After all, the most significant degree of captivity is that to bus in the low-income segment where there is an estimated probability of 0.14 of captivity to that mode. To arrive at this figure, the first term on the right of Expression 2 was used so that the likelihood of captivity to bus is 0.167/1.90 ≈ 0.14.

Independent Availability Logit Model

Table 3 gives the estimation results for the independent availability logit model. First, models for the full data set will be compared. Unlike the captivity model, the independent availability model provides a significantly better fit to the pooled sample than does the standard logit model: the hypothesis that the availability parameters are all jointly one (indicating deterministic availability of all alterntives in M_n for all individuals) is rejected at the 95 percent level. This improvement is explained by the independent availability model's complete representation of the choice set structure as opposed to the extreme assumption underlying the captivity model of the previous section.

Again, as in the case of the logit captivity models, a general increase in the magnitude of the choice model parameters is noted. In the independent availability model, this increase is attributable not only to consideration of captivity but also to consideration of all of the trade-off situations that each decision maker can possibly face. For example, if an individual has available bus (B), taxi (T), and automobile passenger (AP), not only is there a probability that his choice of bus is from the set (B,T,AP), but there is now a probability that the choice is from (B,T) and (B,AP).

The improvement in fit provided by the pooled independent availability logit model, albeit statistically significant, is certainly not dramatic (the chi-squared statistic is 11.8 with 4 degrees of freedom, compared with a critical value of 9.5 at a 95 percent signficance level). Once again, this has led to segmentation of the sample of workers along the income dimension and estimation of separate models for each (Table 3). The hypothesis that all of the parameters are equal across income segments can be rejected at the

TABLE 3 MACEIÓ HOME-BASED WORK TOUR MODE CHOICE MODEL—INDEPENDENT AVAILABILITY LOGIT

	Estimated Parameters			
	Low Income	Medium Income	High Income	Pooled
Choice Model Parameters				
Alternative-specific constants				
Bus	0	0	0	0
Taxi	1.35 (0.6)	-1.28 (-0.5)	1.75 (1.1)	-0.44 (-0.3)
Automobile passenger	-1.80 (-0.7)	-3.41 (-1.9)	-2.28 (-1.9)	-2.91 (-6.6)
Automobile driver	1.75 (0.8)	1.20 (0.5)	0.46 (0.4)	0.82 (1.1)
Total travel time (min/day)	0.005 (0.4)	-0.017 (-2.5)	-0.015 (-2.1)	-0.015 (-3.5)
Total travel cost (Cr$ 1977/day) divided by ℓn(household income, KwH/month)	-0.238 (-1.2)	-0.336 (-3.8)	-0.450 (-2.9)	-0.325 (-5.2)
Household income (KwH/month)				
Bus	0	0	0	0
Taxi	0.022 (0.6)	-0.010 (-0.4)	0.001 (0.4)	0.005 (2.3)
Automobile passenger	0.037 (1.3)	0.017 (0.9)	0.003 (1.0)	0.007 (4.3)
Automobile driver	0.018 (0.9)	0.040 (1.5)	0.001 (0.2)	0.007 (3.5)
No. of household members				
Bus	0	0	0	0
Taxi	-1.35 (-1.6)	0.18 (1.6)	-0.34 (-2.4)	-0.11 (-1.8)
Automobile passenger	-0.57 (-2.0)	-0.17 (-1.7)	-0.17 (-1.8)	-0.15 (-2.9)
Automobile driver	-0.36 (-1.4)	-0.83 (-2.9)	-0.23 (-1.9)	-0.31 (-3.3)
Automobile availability (cars/workers)				
Bus	0	0	0	0
Taxi	4.70 (2.6)	1.31 (1.3)	2.19 (2.2)	2.06 (3.4)
Automobile passenger	4.55 (2.6)	2.39 (5.6)	5.40 (5.6)	3.59 (8.2)
Automobile driver	2.20 (2.0)	2.03 (2.4)	7.25 (5.0)	5.11 (5.5)
CBD work location and lunch trip home				
Bus	0	0	0	0
Taxi	0.0 (0.0)	0.3 (0.6)	1.5 (2.3)	0.7 (2.0)
Automobile passenger and driver	-0.6 (-0.6)	-0.7 (-1.6)	-0.1 (-0.2)	-0.3 (-1.2)
Female worker				
Bus, taxi, automobile passenger	0	0	0	0
Automobile driver	-2.1 (-1.9)	-2.9 (-3.3)	-2.7 (-4.1)	-3.1 (-5.1)
Professional worker and lunch trip home				
Bus	0	0	0	0
Taxi	-0.7 (-0.4)	0.4 (0.6)	1.8 (2.7)	0.9 (2.1)
Automobile passenger and driver	1.3 (1.3)	0.7 (1.6)	1.8 (3.5)	1.1 (3.8)
Availability Parameters				
Bus	0.98 (129.8)	1.00	1.00	1.00
Taxi	1.00	1.00	0.69 (2.4)	0.50 (1.0)
Automobile passenger	0.36 (1.4)	1.00	0.81 (7.3)	0.88 (7.9)
Automobile driver	1.00	0.87 (12.1)	0.87 (24.5)	0.83 (28.6)
Summary Statistics				
Log-likelihood at β=0, γ=1	-596.5	-532.8	-649.8	-1779.0
Log-likelihood at convergence	-126.3	-263.3	-311.7	-715.0
Rho-squared	0.7882	0.5565	0.5203	0.5981
Adjusted rho-squared	0.7531	0.5190	0.4865	0.5857

Note: Asymptotic *t*-statistics in parentheses.

95 percent significance level, so it has been a definite statistical improvement to segment the sample.

When interpreting the availability parameters in Table 3, it should be kept in mind that deterministic alternative availability rules have been applied to construct choice sets for the estimation sample. For example, the low-income segment independent availability model has estimated a probability of availability of 1.0 for the automobile driver mode; however, as was stated before, only individuals from automobile-owning households who are 18 years or older actually have the automobile driver alternative deterministically available. Thus the correct interpretation of this specific parameter is that the best fit to the observed modal choices in the low-income segment is achieved when a probability of 1.0 is assigned to the availability of the automobile driver mode, given that it is deterministically available to the decision maker. Similarly, in the high-income group, the probability of availability of the automobile driver mode is estimated to be about 0.87 for those who have the alternative in their set M_n. This value contrasts with the probability of availability of 1.0 assigned to this alternative in the standard logit model.

Comparison of Alternative Probabilistic Choice Set Models

In this subsection the independent availability logit income segment models will be compared with the logit captivity models. Although it is possible to perform a formal statistical test (recall, however, that the logit captivity specification is not nested within the independent availability model) the two specifications can be compared using a corrected likelihood ratio based on the Akaike information criterion (AIC). This latter measure, defined as the log-likelihood at convergence minus the number of parameters in the model, was first proposed by Akaike *(9)* and is discussed in Amemiya *(10)*. It can be used to compare nonnested hypotheses; the model with the larger value of AIC is preferred.

Alternately, use can be made of an adjusted likelihood ratio index ($\bar{\rho}^2$) based on the AIC and defined as

$$\bar{\rho}^2 = 1 - [L(\hat{\beta}) - K]/L(0) \quad (5)$$

where

$L(\hat{\beta})$ = the log-likelihood of the sample at the maximum likelihood estimates $\hat{\beta}$ of the parameters,
$L(0)$ = the log likelihood of the sample assuming equal probability of choice for all alternatives, and
K = the number of parameters in β.

Following an analysis identical to that of Horowitz *(11)*, it can be shown that if the $\bar{\rho}^2$ of two nonnested models differ by 0.002 or more for a sample of 1,147 observations and a four-alternative choice context, then almost certainly the model with the lower $\bar{\rho}^2$ is incorrect.

The three market segment logit captivity models have a joint $\bar{\rho}^2$ of 0.586 compared with 0.586 for the income segment independent availability logit models. In the aggregate there appears to be no difference between the two probabilistic choice set models.

The following table gives the $\bar{\rho}^2$-values for the individual choice set formation models by income segment, pooled income segments, and the pooled models.

	$\bar{\rho}^2$				
Model	*Low*	*Medium*	*High*	*All*	*Pooled*
Logit	0.752	0.519	0.480	0.583	0.584
Logit captivity	0.757	0.519	0.484	0.586	0.584
Independent availability logit	0.753	0.519	0.487	0.586	0.586

For the sample sizes in each segment, a difference in $\bar{\rho}^2$ of 0.002 is still significant. Hence the logit captivity model performs better than the independent availability logit model in the low-income group; the reverse is true in the high-income group; and in the middle-income group the choice between the two models is indifferent.

This result highlights an important practical conclusion. It indicates that the restrictions imposed on the probabilistic choice set generation process cannot be arbitrary; instead, they must reflect the population in question and the source of the constraints on it. Hence, in the present context, it would appear reasonable to adopt the logit captivity model for both the low- and medium-income groups (for the latter group, the decision is arbitrary) and the independent availability specification for the most unconstrained group, the high-income segment of the workers.

A last comparison between the two types of probabilistic choice set models is given in Table 4, in which the predicted choice set probabilities according to the logit captivity and independent availability logit models are given (both for the pooled data set and for the three income segments). The table has two parts, the first of which corresponds to a decision maker with all four modal alternatives in M_n and the second of which corresponds to an individual without the automobile driver alternative.

Although many useful inferences can be drawn from the table, one of the most interesting comes from the first part for the independent availability model for the high-income segment. This group is naturally the one that displays the higher rate of automobile ownership and is therefore the one in which workers will most often have the automobile driver alternative allocated to them by the choice set construction rules. Yet, for these individuals, there is predicted a less than 50 percent chance that they will actually be selecting from the full choice set that includes automobile driver, as opposed to the usual assumption of 100 percent in a standard choice model. Medium-income workers who have the automobile driver alternative available, on the other hand, are predicted to have a probability of 87 percent of choosing from the full choice set of four alternatives. A third observation can be made concerning low-income workers who have bus, taxi, and automobile passenger available. The choice set construction rules adopted allowed automobile passenger to all workers; there is only a 35 percent chance, however, that a low-income worker with this three-alternative M_n actually chooses from M_n. It is nearly twice as likely that he will choose between bus and taxi instead.

Another pattern of note in Table 4 is the decrease in probability of captivity to the bus mode with increases in income, as predicted by the logit captivity specifications by income group. Such a result, although intuitively plausible and in conformance with the constraint-based view of choice set formation, also indicates that some parameterized version of the captivity model, in which captivity is expressed as a function of independent variables (among them income), might result in statistically better models.

It has been shown that probabilistic captivity and independent availability choice set models, combined with market segmentation, result in statistically superior models compared with the standard logit model. This result holds in spite of apparent weaknesses in the choice set models (i.e., the strong assumption of independence of alternative availability, or the extreme scenario of captivity or full choice).

TABLE 4 PREDICTED CHOICE SET PROBABILITIES

	Logit Captivity				Independent Availability Logit			
Choice Set	Pooled	Low	Medium	High	Pooled	Low	Medium	High
Available Alternatives: B, T, AP, AD								
B	0.013	0.141	0.085	0.011	0.010	0	0	0.008
T	0.004	0.013	0.009	0.006	0	0	0	0
AP	0.008	0.006	0.050	0.041	0	0	0	0
AD	0	0	0	0	0	0	0	0
Full	0.976	0.840	0.857	0.942	0.366	0.351	0.868	0.485
All others	0	0	0	0	0.624	0.649	0.132	0.507
Available Alternatives: B, T, AP								
B	0.013	0.141	0.085	0.011	0.062	0	0	0.059
T	0.004	0.013	0.009	0.006	0	0.010	0	0
AP	0.008	0.006	0.050	0.041	0	0	0	0
Full	0.976	0.840	0.857	0.942	0.441	0.351	1.000	0.559
All others	0	0	0	0	0.497	0.639	0	0.382

Note: B = bus, T = taxi, AP = automobile passenger, and AD = automobile driver.

On the other hand, the additional difficulty of calibrating a choice model with probabilistic choice sets can be significant compared with estimating the parameters of a standard choice model. The loss of certain convenient properties of the log-likelihood function of the sample creates serious obstacles for the analyst and jeopardizes the practical usefulness of probabilistic choice set models in general.

Thus it is necessary to go beyond measures of statistical significance to evaluate the practical significance of probabilistic choice set modeling. To do so, the predictions produced by the different models are compared in the following section.

MODEL PREDICTION RESULTS

The predictions of the income segment logit models (Table 1) are compared with the probabilistic choice set specifications that are statistically best for each income group (i.e., the logit captivity models of Table 2 for the low- and medium-income groups and the independent availability logit specification of Table 3 for the high-income group). The two sets of models are used to predict changes in modal shares due to

1. Uniform changes (two levels, low and high) across the population for travel time;
2. Implementation of a specific policy alternative; and
3. Shifts in the distributions of a socioeconomic variable, specifically income.

Uniform Changes in Travel Time and Cost

Two levels of change in travel time are implemented herein, 10 percent (low) and 100 percent (high). The reason for this two-level test is that the benefits of choice set modeling may be nonlinear and appear only under conditions of extreme change in these variables.

Table 5 gives the predicted changes under a 10 percent travel time increase for the income segment logit and the income segment choice set specifications, respectively. The results are presented both by income segment and over the entire sample of workers.

If the low-income predictions are studied, it can be noted that the changes in ridership from the logit captivity formulation are less than or equal to the corresponding prediction from the standard logit model for the group; this is to be expected, of course, given that the predicted degree of captivity to bus is highest in this segment of the workers, for which this mode is also the most frequently chosen. The estimation sample of 528 workers in the low-income segment has an observed frequency of choice of bus of 88 percent, so it is understandable that the dampening effect mentioned is present. The predictions are average changes: error bounds have not been provided for these measures because the differences are small between models (with few exceptions) and it is reasonable to assume that none of the differences are statistically significant at any reasonable level of significance. Even in the case of the taxi mode, for which there is a 100 percent difference in the predictions of the two models, it is unlikely that they are statistically different because this mode is the least well explained by any of the models presented.

For the medium-income segment of the Maceió workers, the opposite result has been found: namely, the choice set specification in general states that the medium-income workers are more sensitive to the 10 percent travel time increase than predicted by the standard logit specification. This segment, like the low-income group, has a high incidence of choice of bus (67 percent), but the choice set specification predicts a smaller degree of captivity in this group compared with the low-income segment. At the same time, the travel time coefficients in the income segment logit and logit captivity specifications differ by a factor of almost 3. However, it again appears that the predicted differences are not significant.

The high-income segment is also predicted to be more sensitive to the 10 percent travel time increase by its independent availability model than by the standard logit specification.

In aggregate, the data in Table 5 show a tendency of the standard logit specification to underpredict the effect of travel time increases on the worker population compared with the choice set model. The source of this disparity between the models is the medium- and high-income groups, which the choice set models predict to be more sensitive to the change than does the logit formulation. Because of the aggregation, the overall changes in demand predicted to occur by each set of models are even more uniform than if viewed by income segment, as has just been done.

TABLE 5 PREDICTED IMPACT (% change in demand) OF 10 PERCENT TRAVEL TIME INCREASE

	Predicted Response in Mode							
	Bus		Taxi		Automobile Passenger		Automobile Driver	
Change in Mode	L	PCS	L	PCS	L	PCS	L	PCS
Low income (<80 KwH/month)								
Bus	-0.3	-0.2	3.3	1.7	4.0	3.4	1.4	0.8
Taxi	0.1	0	-3.3	-1.7	0	0	0.3	0.3
Automobile	0.1	0.1	0.8	0.8	-1.3	-1.4	-0.6	0
Medium income (80-130 KwH/month)								
Bus	-1.8	-2.6	6.7	12.8	6.6	7.3	1.9	2.8
Taxi	0.3	0.6	-6.7	-12.3	0.3	0.1	0.2	0.2
Automobile	0.5	0.6	0.6	0.6	-1.8	-1.5	-0.9	-1.3
High income (>130 KwH/month)								
Bus	-2.3	-2.3	3.2	4.4	1.9	2.7	0.6	0.4
Taxi	0.4	0.6	-6.0	-6.4	0.4	0.6	0.2	0.1
Automobile	0.6	0.6	1.2	1.2	0.7	-0.3	-0.8	-0.4
Overall								
Bus	-1.1	-0.3	4.2	6.6	3.7	4.3	1.0	1.0
Taxi	0.2	0.3	-5.6	-7.3	0.3	0.4	0.2	0.2
Automobile	0.3	0.3	0.9	0.9	-0.3	-0.8	-0.8	-0.6

Note: L = logit model and PCS = probabilistic choice set model.

TABLE 6 PREDICTED IMPACT (% change in demand) OF 100 PERCENT TRAVEL TIME INCREASE

	Predicted Response in Mode							
	Bus		Taxi		Automobile Passenger		Automobile Driver	
Change in Mode	L	PCS	L	PCS	L	PCS	L	PCS
Low income (<80 KwH/month)								
Bus	-3.7	-2.5	40.8	13.3	54.7	54.4	12.3	6.4
Taxi	0.6	0.2	-30.0	-12.5	1.3	1.4	1.7	0.8
Automobile	0.7	0.5	3.3	2.5	-11.3	-10.9	-5.7	-2.5
Medium income (80-130 KwH/month)								
Bus	-20.7	-36.5	84.9	219.0	88.2	144.8	14.2	14.5
Taxi	2.4	3.3	-49.7	-63.1	2.0	1.3	0	1.1
Automobile	4.6	5.1	4.5	5.6	-12.0	4.8	-11.4	-20.2
High income (>130 KwH/month)								
Bus	-21.8	-24.1	34.3	49.2	22.3	28.6	4.9	3.2
Taxi	3.4	4.8	-45.4	-48.4	3.3	4.0	1.4	0.7
Automobile	6.4	5.6	14.3	9.6	14.3	2.7	-9.6	-5.3
Overall								
Bus	-12.4	-17.3	52.4	96.7	47.6	69.7	7.8	6.2
Taxi	1.7	2.0	-43.5	-45.4	2.6	2.8	1.3	0.8
Automobile	3.0	2.9	8.9	6.7	2.6	1.7	-9.7	-8.6

Note: L = logit model and PCS = probabilistic choice set model.

Next, the differences in model predictions under a high (100 percent) uniform perturbation in travel time are considered. Table 6 gives the model predictions due to a large change in travel time for the income segment logit and choice set specifications. Note that the income segment logit specification predicts that a uniform doubling of automobile travel time results in more than an 11 percent decrease in demand for both the automobile passenger and the automobile driver modes. The corresponding prediction for the choice set models, however, shows a 20 percent loss of demand in the automobile driver mode and about a 5 percent increase in demand for the automobile passenger mode. Thus the standard logit specification for the medium-income group suggests that a 100 percent increase in automobile travel time causes a shift away from the mode entirely; the captivity specification, however, suggests that there will instead be a shift within the automobile mode via the mechanism of increased ridesharing.

Careful study of Table 6 does bring to light one interesting pattern of differences between the two sets of models. Note that in the aggregate prediction results the income segment logit specification generally predicts a smaller response to a doubling of bus travel time than predicted by the choice set specifications; conversely, a 100 percent increase in automobile travel time is said to result in greater changes than predicted by the choice set models. Further study indicates that these aggregate-level differences between the two models stem from identical patterns in the income groups, though both of the effects mentioned are not necessarily present in each segment. What is observed here is perhaps the result of a twofold effect:

1. The choice set specifications predict a greater response to a change in bus travel time because of the increased sensitivity that these models display to travel impedance compared with the standard logit specifications (compare the travel time coefficients of Table 1 to those of Tables 2 and 3, noting that the former are uniformly less in absolute value than the latter) and
2. The choice set models predict a smaller impact of changing automobile travel time because of their fuller consideration of alternative availability (i.e., an individual's captivity to the automobile passenger mode makes him insensitive to changes in the mode's travel time).

Swait *(12)* reports prediction tests analogous to these two model systems but involving the travel cost variable. The inferences to be drawn from those results are identical to the ones drawn here for travel time.

The results presented thus far are not supportive of any strong superiority of the probabilistic choice set specifications to the standard logit formulation for the choice dimension being examined. Certain differences of note between the predictions of the two model systems have been pointed out, but they may not be worth the extra effort necessary to estimate probabilistic choice set models. On the other hand, neither is the uniform change scenario reflected in the previous predictions necessarily a realistic one for application of these models. This has led to testing for differences in predictions when the two model systems are applied in the context of evaluation of a specific policy scenario.

Evaluation of a Specific Policy

The policy scenario to be used in this subsection is inspired by an actual policy evaluation previously reported by Geltner and Swait *(13)* for Maceió. The specific policy considered envisions extensive traffic engineering improvements in the central business district (CBD) of the city, including the implementation of "bus only" streets and improved loading and unloading spaces and procedures and prohibition of parking of private automobiles in certain areas of the CBD. The impact of such changes is assumed to affect trips to and through the CBD in the following manner:

1. Bus trips—decrease of 10 min per leg of the trip due to improved flow of traffic,
2. Automobile trips—increase of 5 min per leg due to increased walking distances in the CBD, and
3. Taxi trips—no effect.

Table 7 gives the predicted average impacts of implementing this policy. In the first part of the table the predictions of the logit models are given, and in the second part those of the choice set models are given. The income segment logit specification understates the impact of the policy on the bus and taxi modes for the medium- and high-income groups and conversely overstates

TABLE 7 PREDICTED IMPACT (% change in demand with respect to base case) OF CBD IMPROVEMENT POLICY ALTERNATIVES

	Predicted Response in Mode			
	Bus	Taxi	Automobile Passenger	Automobile Driver
Income segment logit specification				
Low income	0.8	-5.0	-10.0	-4.3
Medium income	5.4	-15.6	-16.9	-8.0
High income	8.3	-4.4	-6.9	-3.2
Overall	3.6	-8.4	-10.5	-4.4
Income segment probabilistic choice set specifications				
Low income	0.5	-1.7	-12.0	0.0
Medium income	7.2	-30.2	-12.3	-12.8
High income	8.5	-10.0	-8.7	-2.3
Overall	4.0	-14.7	-10.3	-4.6

the impacts on the low-income group compared with the corresponding choice set model predictions. This result can be explained by the sensitivity of the medium- and high-income groups to travel time in the choice set models being greater than the alternative availability effect; the opposite holds in the low-income group. For the private modes there is no such clear-cut pattern. In either case, however, it is unclear that any of the observed differences in predictions between model systems is actually statistically significant.

This result is not unexpected given the homogeneity of predictions presented previously for uniform changes in travel time. It has been hoped that by targeting a specific group of the workers' population, namely those working in the CBD or traveling through it to reach their workplace, significant differences between the model systems could be detected. It is possible, however, that differences would indeed be found if the impacts on only CBD workers or those traveling through that part of the city were examined.

Shifts in a Socioeconomic Characteristic

In the previous two subsections differences in predictions between the two model systems under consideration have been evaluated in contexts that could best be labeled short range. In both cases, although certain trends are apparent, it remains unclear if one of the model systems is undoubtedly superior to the other. The purpose of this section is to evaluate the differences when the simulated scenario corresponds to long-range shifts in the composition of the worker population in Maceió. Specifically, two different shifts in income distribution will be simulated.

Table 8 gives the observed worker household income distribution and the postulated shift in that distribution. This hypothesis represents a significant worsening of income distribution compared with the observed case. The shift in income distribution is simulated by assigning a weight to each observation corresponding to the ratio of the postulated to the observed frequency for its income group (e.g., 16.9/15.1 for the lowest income category). Note that the actual income value of an observation is not changed, merely the weight given to the predictions for the observation. This methodology assumes that all other characteristics remain constant within the sample (e.g., there are no accompanying shifts in the conditional automobile ownership distribution).

Table 9 gives the predictions for the income shift scenario for each of the model systems. Comparison of the two parts of the table shows little or no difference in the predictions of the standard logit versus choice set specifications.

TABLE 8 OBSERVED AND POSTULATED INCOME DISTRIBUTIONS FOR MACEIÓ WORKERS

Income Category (KwH/month)	Observed Distribution (%)	Scenario Distribution (%)
0-40	15.1	16.9
41-60	9.0	16.9
61-80	12.4	13.5
81-100	12.5	13.5
101-120	13.5	10.2
121-150	12.5	10.2
151-200	10.2	9.3
201-250	5.6	3.4
251-300	2.7	2.7
>300	6.5	3.4
Total	100.0	100.0

Though not presented here, another simulation of a shift in automobile ownership distribution has been carried out with similar results across the two model systems.

CONCLUSIONS

This study was aimed at evaluating the statistical validity of modeling probabilistic choice set formation when the representation of alternative availability is particularly simple (i.e., a single parameter). The estimated models presented here indicate a need to further investigate modeling choice set formulation, particularly in environments such as Maceió, where the traveling pubic is subject to significant constraints of many types that cannot be observed. The choice set formation stage should be of even greater importance in the more discretionary types of behavior, such as mode and destination choice and trip generation for shopping.

Market segmentation, although an indispensible technique to improve the explanatory power of the choice models for a population with taste variations, is too crude a tool to, alone, substitute for explicit models of choice set formation. Allied to the latter, however, market segmentation is of great value. In the empirical work presented here, income segmentation of the sample results in a greater incremental improvement in model fit than is provided by the choice set models that have been tested; nonetheless, it has been demonstrated for this data that choice set modeling provides a statistically significant increase in explanatory power of the work mode choice model system for Maceió.

Another result of the empirical work in Maceió is the confirmation of the important effect of the assumption of choice set struc-

TABLE 9 PREDICTED IMPACT (% change of demand with respect to base case) OF INCOME DISTRIBUTION SHIFT SCENARIO

	Predicted Response in Mode			
	Bus	Taxi	Automobile Passenger	Automobile Driver
Income segment logit specification				
Low income	30.8	29.2	25.3	24.9
Medium income	-9.0	-8.4	-11.2	-10.6
High income	-18.3	-20.7	-26.5	-26.2
Overall	9.3	-6.0	-15.1	-17.7
Income segment probabilistic choice set specifications				
Low income	30.7	26.7	23.3	28.6
Medium income	-9.6	- 8.4	-10.0	- 9.3
High income	-18.3	-21.9	-27.1	-25.9
Overall	9.1	-6.9	-15.3	-16.8

ture on the explanatory power of the full choice model. A strategy that combines market segmentation and appropriate choice set restrictions appears to be most likely to work well, and the logit captivity model appears best for the low-income group, whereas the independent availability logit specification appears to be superior for the high-income group.

This factor may indeed be the reason for the inability of the choice set specifications to present clearly predictions that differ from the standard logit specifications under the various policy scenarios considered. Despite the statistical superiority of the choice set models compared with the standard logit models, it is thought that the homogeneity of the predictions across the two model systems is due in part to limitations of the choice set structure representation inherent in the captivity and independent availability models. Perhaps the assumptions made by each of these choice set models, although somewhat better than the deterministic choice set representation of traditional discrete choice models, are nonetheless inappropriate (even simplistic) for the populations in question. Further, the representation of the impact of constraints via single parameters per alternative is a restrictive and simplistic representation of a complex process. As indicated by Swait and Ben-Akiva *(3)*, the alternative route of parameterization of the availability functions may be more fruitful for further work than is the present approach.

A drawback of the choice set formation models is the greatly increased difficulty of calibrating them. The departure from the standard logit linear-in-parameters formulation can be costly because the convenient property of concavity of the log-likelihood function, which guarantees the uniqueness of the parameters at the point of convergence, is lost. Hence a greater degree of care and sophistication on the part of the analyst is necessary, not to mention specialized estimation software.

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REFERENCES

1. J. Swait, V. Kozel, R. Barros, and M. Ben-Akiva. A Model System of Individual Travel Behavior for a Brazilian City. *Transportation Policy and Decision Making* (forthcoming).
2. M. Ben-Akiva and J. Swait. Choice Models with Simple Probabilistic Choice Set Generation Processes. Submitted for publication to *Transportation Research B*.
3. J. Swait and M. Ben-Akiva. Incorporating Random Constraints in Discrete Choice Models: An Application to Mode Choice in São Paulo, Brazil. Working Paper. Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, 1984.
4. C. Manski. The Structure of Random Utility Models. *Theory and Decision*, Vol. 8, 1977, pp. 229–254.
5. M. Ben-Akiva. Choice Models with Simple Choice Set Generating Processes. Working Paper. Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, 1977.
6. M. Gaudry and M. Dagenais. The Dogit Model. *Transportation Research*, Vol. 13B, 1979, pp. 105–111.
7. D. Geltner and R. Barros. Travel Behavior and Policy Analysis in a Medium Size Brazilian City. *Transportation Policy and Decision Making* (forthcoming).
8. M. Ben-Akiva, H. Gunn, and L. Silman. "Disaggregate Trip Distribution Models." *Proc., Japan Society of Civil Engineers*, No. 347/IV-1, July 1984, pp. 1–16.
9. H. Akaike. "Information Theory and an Extension of the Maximum Likelihood Principle." In *Second International Symposium on Information Theory* (B. N. Petrov and F. Csaki, eds.), Akademiai Kiado, Budapest, Hungary, 1973, pp. 267–281.
10. T. Amemiya. Selection of Regressors. *International Journal of Economic Literature*, Vol. 19, 1980, pp. 1483–1536.
11. J. Horowitz. Statistical Comparison of Non-Nested Probabilistic Discrete Choice Models. *Transportation Science*, Vol. 17, No. 3, 1983, pp. 319–350.
12. J. Swait. *Probabilistic Choice Set Generation in Transportation Demand Models*. Ph.D. dissertation. Massachusetts Institute of Technology, Cambridge, 1984.
13. D. Geltner and J. Swait. *Illustrative Policy Analysis: Applications of a Disaggregate Mode Choice Model for Work Trips in Maceió, Brazil.* Studies of Urban Travel Behavior and Policy Analysis in Maceió, Vol. 3. Center for Transportation Studies, Massachusetts Institute of Technology, Cambridge, 1981.

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