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Contents

Foreword

This Record contains papers on travel demand forecasting, travel behavior, and mode choice analysis. One paper discusses a method for coding transit system access links. Two papers discuss travel demand forecasting techniques, one using dynamic microsimulation, the other forecasting traffic in a large metropolitan area on the basis of trip diary information. One paper discusses a fixed-point approach to the problem of estimating freeway origin-destination matrices. Finally, five papers discuss aspects of travel behavior and mode choice, using multivariate cluster analysis, stated preference models, calibration of semicompensating mode choice models, variability of individual trip scheduling, and applications of teleworking in changing travel behavior.

How To Code the Generalized Cost of Accessing a Transit System

ANTTI TALVITIE

A method of coding generalized cost transit system access links is described, and the advantages of using large zones in transportation planning are demonstrated. Use of large zones is motivated by the expense (in time and money) of making travel demand forecasts. The method was developed concurrently with the models for predicting the values of the access link times for rail and bus trips. These supply models estimate the in-vehicle times on automobile and bus and the out-of-vehicle times for bus and rail access links using zonal and modal characteristics. Use of different zone sizes is evaluated by a correlation analysis between the predicted and the actual number of rail riders. The results indicate that there is a high correlation between the predicted and actual number of users; the error increases with the zone size, but the increase is small. Error sources independent of zone size also exist; these errors are discussed in detail. It appears that large zone sizes can profitably be used in transportation planning. The access supply models used are very simple. A more complex set of models has been developed. The reason for reporting this simple model is validation. Data collected in extant transportation studies focus on the demand side and made the validation of supply side models impossible. In the present study the data are rich enough but date back to the late 1960s. Good methods are timeless, however.

Today it is a common planning practice to use zone sizes of 1 mi^2 or less in area. The principal reason for using small zones is to reduce the inaccuracies deriving from the access links, to reduce the within-zone variance. However, the access links remain a large error source in travel demand forecasting (*1*). The purpose of this study is to describe a systematic method to calculate the values of the access links and show that larger zones can be used effectively in the planning process. The soundness of using larger zones is made possible by supply models (*2,3*). The supply models are based on the characteristics of the zone and the transport system serving it and make explicit the intrazonal transportation system, which is needed to enable the use of large zones without losing accuracy. In fact, accuracy may be gained by the explicit modeling of intrazonal transportation system, not by using smaller zones.

The use of large zones brings with it many advantages, including quicker coding of networks, less chances to make errors in network coding, less expensive traffic assignments (*4–6*), interpretable assignment outputs, more accurate land use projections (*7*), better travel forecasts, and visual control of input data and other data errors. By using the supply models together with access mode/station choice models, reliable forecasts are also possible for access mode and station usage. This information is important for the design of public transportation systems. There has been renewed interest in modeling transportation access networks and access mode choices. Recent work (*8,9*) in modeling transportation access choices and access systems is similar to the present work.

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METHOD AND DATA

Consistent Calculation of Access Link Values

The method to be described for calculating the values of the access links, and the subsequent decomposition of volumes on these links by mode and station, is based on a model system that is estimated in stages with each stage affecting the following stage (the nested logit model).

A joint decision for choosing to travel on access mode a via station s on line (or path) l, by priority mode m, during time h, to destination d with frequency f, is a function of the level-of-service L provided by the system, the activity system attributes A, and socioeconomic attributes of the traveller S. It can be expressed as

$$P(f, d, h, m, l, s, a) = F(L, A, S) \tag{1}$$

This model can be broken into any number of sequences using the theorem of total probability. For example, it can be expressed as a multiplication of models:

$$\begin{aligned} P(f, d, h, m, l, s, a) &= P(a|s, l, m, h, d, f) \\ &\times P(s|l, m, h, d, f) \times P(l|m, h, d, f) \\ &\times P(m|h, d, f) \times P(h|d, f) \times P(d|f) \times P(f) \end{aligned} \tag{2}$$

where

$P(a|s, l, m, h, d, f)$ = access mode choice,
$P(s|l, m, h, d, f)$ = station choice,
$P(l|m, h, d, f)$ = line choice,
$P(m|h, d, f)$ = main mode choice,
$P(h|d, f)$ = hour-of-day choice,
$P(d|f)$ = destination choice, and
$P(f)$ = trip frequency.

This general model system provides a sound framework for estimating access mode, station loadings, transit line choice, choices of mode and destination, and so forth. If some elements are not present in the analysis (e.g., choice of travel hour), that segment of the model system can be dropped without ruining the model system. This paper focuses on the first two models: access mode and access station choices. Other choices are dropped for clarity. The access mode and station selection models are logit models.

Each model has a utility function that includes variables relevant to the choice being modeled. For example, function $U\text{-}a$ describes the utility to travel to a station on Access Mode a. For the sake of example, this function may be made up of the trip time ($T\text{-}a$), cost or fare ($C\text{-}a$), and service headway ($H\text{-}a$). Mathematically,

$$U\text{-}a|s,\ l = b_1(T\text{-}a) + b_2(C\text{-}a) + b_3(H\text{-}a) \quad (3)$$

Once the coefficients b and the values of the explanatory variables are known, $U\text{-}a$ is a number, commonly called a "generalized price" of Mode a. The aggregate, "logitly" consistent generalized price to Station s by all modes is given by the following expression:

$$U|s,\ l = \log(\sum \exp U\text{-}a|s,\ l) \quad (4)$$

Similarly, the access station model may be expressed as follows:

$$U\text{-}s|l = c_1(PKG\text{-}s) + c_2(T\text{-}ss') + c_3(U|s,\ l) \quad (5)$$

where

$PKG\text{-}s$ = parking cost (or parking availability) at Station s, and
$T\text{-}ss'$ = travel time on line haul from Station s to a competing station, s'.

The aggregate "logitly" consistent inclusive price to access a rail (transit) line is

$$U\text{-}l = \log(\sum \exp U\text{-}s|l) \quad (6)$$

Use of Access Mode and Station Selection Models in Network Coding

The objective of the access mode/station selection models is to give a number to be assigned to an access link in coding networks and provide information on access mode and station usage in the zone where travelers reside. This information can be obtained if the traffic zone is connected to the network in a manner consistent with the travel demand models used to characterize not only travelers' access mode/station choice behavior but also the other travel dimensions such as mode and destination choices. In fact, the connection of traffic zones to the network is critical from the point of view of obtaining reliable traffic forecasts by line and mode. It is precisely the inclusive price, developed earlier, that should be used to connect the zone centroids to bus lines or rail stations ($U\text{-}s|l$) or lines ($U\text{-}l$). The difficulty introduced by the egress attributes will be addressed later.

The following examples illustrate how in practice traffic zones should connect to the network in a systematic and consistent manner. Consider a traffic zone served by rail and bus modes. Access to rail stations is by walk, automobile, and bus, whereas walk is the only access mode for bus (this restriction is solely for illustration). The connection of a zone to each rail station (or rail line) is via an access link whose value is a weighted average that is a proper aggregation of the available access modes (and stations). The connection of the zone to bus lines is via a walk access link. In order not to confuse the two modes, presentations of bus and rail are worked separately to point out how $U\text{-}l$, the generalized line price, is calculated for coding the access links.

The bus network is considered first because it is simpler (see Figure 1). The example zone is served by three bus lines, 1, 2, and 3, which are connected to the zone centroid by values U-1, U-2, and U-3. Because there is only one access mode, these are the average zonal walk times to these lines and will be denoted by U-1. These values depend on such factors as zone area, bus spacing, and bus frequency and are obtained directly from the supply models, to be explained shortly.

The calculation of the rail access links requires both access network supply and access mode/station choice models. Consider the rail network in Figure 2. The two rail lines serving the zone can be accessed by walk, automobile, and bus. Bus Lines 1 and 3 can also be used for access purposes. The example zone is thus connected to Rail Lines 10 and 11 by Access Links U-10 and U-11, respectively. To calculate the value of these access links, the access mode/station selection models (Equations 3 and 5) and the values of $T\text{-}a$, $C\text{-}a$, $H\text{-}a$, $PKG\text{-}s$, and $T\text{-}ss'$ are needed. The latter are calculated for each zone as a function of the transportation system serving or planned for the zone. In the present example application a simple parametric access network model is used (*10*) as explained next.

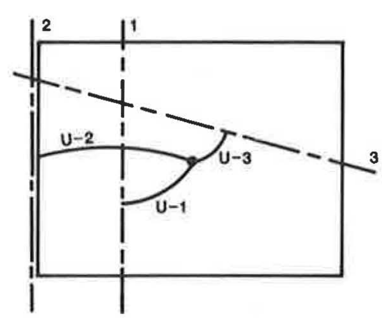


FIGURE 1 Bus network.

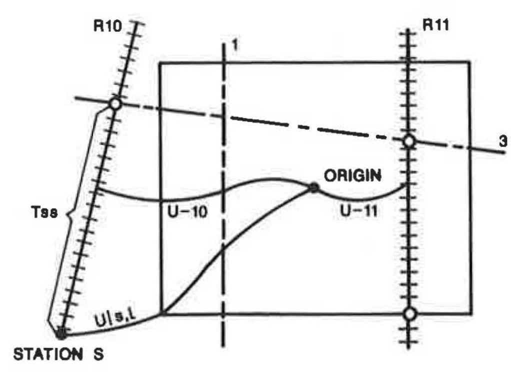


FIGURE 2 Rail network.

Access Supply Models

The access supply models give the mean values for automobile and bus in-vehicle times and bus out-of-vehicle (walk) time. Models for within-zone variances of these variables were also developed for other uses with explicit aggregation procedures, such as sample enumeration (*6*). Only the former models are used here. A summary of the models appears in Table 1. The variables used in these models are shown and defined in Figure 3.

The walk time to a bus stop depends on such variables as distance between stops, spacing between bus lines, and zone size. The model logically shows that increases in all these values increase the walk time to bus. The farther the station is from the zone centroid, the longer are bus ride and car drive times to station. The greater the speed of the vehicle, the shorter are bus ride and car drive times. Depending on whether lines run parallel or perpendicular, one of two equations is used in finding the bus out-of-vehicle and in-vehicle times.

The available data did not permit the use of the more advanced versions of the models here; the use of the more sophisticated access supply models in a different modeling environment can be found elsewhere (*4–6*).

Data Source

The data come from the origin-destination survey conducted in 1969 by W. C. Gilman Company for the Southward Transit Area Coordination Committee (STAC) in Chicago. Three data sets with varying zone sizes are formed from the STAC study. The first data set consists of sixty-eight 1-mi^2 zones and twenty-nine 4-mi^2 zones. This data set is denoted as A(1-4); these were the actual sizes in the original STAC study. The second data set combines 42 square mile zones into thirteen 4-mi^2 zones. This data set is denoted as A(4). The third set of data is the combination of thirty-six 1-mi^2 zones into four 9-mi^2 zones and sixteen 4-mi^2 zones into four 16-mi^2 zones. This data set is denoted as A(16). The combined zones were

TABLE 1 Parametric Supply Models

Walk to Bus Stop (Case 1) :

MEAN $T = .45 + .20\ \mathrm{AREA} - .60\ \mathrm{YI} + 3.35\ \mathrm{SY} + 2.25\ \mathrm{STOPS}$

Walk to Bus Stop (Case 2) :

MEAN $T = .45 + .10\ \mathrm{AREA} - .15(\mathrm{XI} + \mathrm{YI}) + 1.13(\mathrm{SX} + \mathrm{SY}) + 2.32\ \mathrm{STOPS}$

Bus Ride to Rail Station (Case 1) :

MEAN $T = 22.69 - 1.86\ \mathrm{SPEED} + 1.38\ \mathrm{SIDE} - .76\ \mathrm{YI} + 4.05(\mathrm{XCOR} + \mathrm{YCOR})$

Bus Ride to Rail Station (Case 2) :

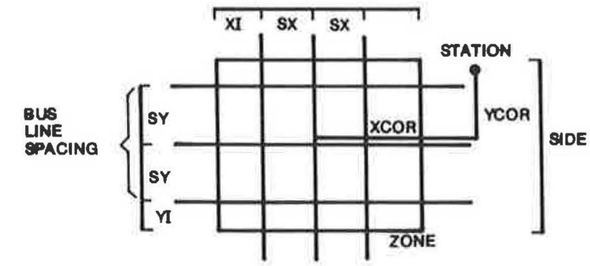
MEAN $T = 17.90 - 1.53\ \mathrm{SPEED} + 1.81\ \mathrm{SIDE} + 3.67(\mathrm{XCOR} + \mathrm{YCOR})$

Drive to Rail Station :

MEAN $T = 10.55 + .37\ \mathrm{AREA} - .52\ \mathrm{SPEED} + 2.67\ \mathrm{DUMMY} + 1.95(\mathrm{XCOR} + \mathrm{YCOR})$

Variable definitions:

AREA	the area of the zone in square miles
XCOR, YCOR	the coordinates of the station from the centroid of the zone in miles
SIDE	the side of the zone in miles
SPEED	speed on arterials in miles per hour
SX, SY	spacing of the bus lines in miles
YI or XI	the distance from zone boundary to the nearest bus line in miles; it is negative if the bus line is outside the zone
STOPS	the number of bus stops per mile
DUMMY	a variable to identify whether or not the station is inside the zone, it equals 0 if station is inside the zone, and 1 if station is outside the zone



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STOPS	the number of bus stops per mile
DUMMY	a variable to identify whether or not the station is inside the zone, it equals 0 if station is inside the zone, and 1 if station is outside the zone

FIGURE 3 Variables used in supply equations.

picked at random with the criteria that the zones were connected to one another. Also taken from the STAC report are the number of people going to each rail station by mode (walk, automobile, or bus).

ESTIMATION OF MODELS AND EVALUATION OF RESULTS

In this section the travel demand model system and the supply models just described are evaluated in various ways to gauge how well equations portray supply and, in particular, whether zone sizes can be increased without compromising accuracy. First, the access mode/station choice models are developed. Second, the travel demand model system is applied; this model incorporates the supply models and the access mode/station choice models. Third, several indices are used to evaluate the results with the three data sets.

Access Mode Model

Logit access mode models were developed for choices between walk, automobile, and bus access modes. Alternative model specifications were considered even though no socioeconomic data were available. The most satisfactory model resulted when it was assumed, as suggested by data, that persons who reside within a ½-mi radius of a rail station walk to that station. This three-mode model is given by

$$\text{Mode choice:} \begin{cases} \text{Walk} \quad \text{if distance to station} < ½\text{ mi} \\ P(m = \text{automobile, bus} \mid s, l) \\ \quad \text{if distance to station} > ½\text{ mi} \end{cases} \tag{7}$$

Two of the estimated models are given in Table 2. The difference between the models is that in Model I there is a constant bus fare of 30 cents, whereas in Model II the bus fare is zero. The values of the time variables, with the exception of the automobile out-of-vehicle time (which was set to a constant 2.5 min), were generated by the supply equations reported earlier.

Statistical tests indicate that all the variables in Models I and II are significant at a .99 level of confidence. Similarity is also found in comparisons of the residuals and the implied values of time for out-of-vehicle and in-vehicle times from the two models. Model I was used in this research.

Station Choice Model

The functional form of the station choice model is given by Equation 5. The results in Table 3 indicate two models whose difference is in the value of $U|s, l$. In Model I, $U|s, l$ is the composite of automobile and bus modes, and in Model II $U\text{-}s|l$ is the composite of all three modes (walk, automobile, and bus). For Model II, the walk utility was computed by using the relationship

$$P(w) = \exp(U\text{-}w)/\sum \exp(U\text{-}a)$$
$$a = \text{walk, automobile, bus} \tag{8}$$

$$\exp(U\text{-}w) = (1 - \text{Cov})[\exp(U\text{-}a) + \exp(U\text{-}b)]/\text{Cov} \tag{9}$$

where

$P(w)$ = the probability that walk was chosen as the access mode,

TABLE 2 Two Estimated Access Mode and Station Choice Models

Coefficients and Relevant Information of the Access Mode Models

Variable	Model I Coefficient	Model I Standard Error	Model II Coefficient	Model II Standard Error
Out-of-vehicle time	-0.115	0.011	-0.108	0.011
In-vehicle time	-0.027	0.007	-0.045	0.008
Cost	-0.082	0.007	-0.094	0.009
Auto bias	-0.293	0.228	2.855	0.200

# of observations for both models 291

Model I

L (0) = -3890 (log likelihood for coefficient of zero)
L (0) = -1310 (log likelihood for estimated coefficients)

Model II

L (0) = -3890 (log likelihood for coefficients of zero)
L (0) = -1280 (log likelihood for estimated coefficient)

Coefficients and Relevant Information of the Station Choice Models

Variable	Model I Coefficient	Model I Standard Error	Model II Coefficient	Model II Standard Error
PKG	0.367	0.037	0.638	0.029
T-ss'	-0.047	0.002	-0.040	0.002
ln p^m	1.000		1.000	

# of observations for both models 291

Model I

L (0) = -7510 (log likelihood for coefficients of zero)
L (0) = -6770 (log likelihood for estimated coefficients)

Model II

L (0) = -15100 (log likelihood for coefficients of zero)
L (0) = -14200 (log likelihood for estimated coefficients)

TABLE 3 Error Measures for Predicted Access Mode and Station Volumes

	R(t-value)	Ave.Vol.	AE	|AE|	SD	RMSE
Walk						
A(1-4)	.98 (90.1)	19.0	-0.01	4.2	10.5	10.5
A(4)	.89	20.7	0.01	10.3	20.1	20.1
A(9-16)	.94	20.6	0.00	14.6	29.8	29.8
Auto						
A(1-4)	.94 (49.3)	18.5	-0.23	4.8	9.4	9.4
A(4)	.74 (10.8)	24.6	-0.33	7.4	14.8	14.8
A(9-16)	.88 (16.9)	62.2	-0.29	14.6	27.4	27.4
Bus						
A(1-4)	.71 (17.9)	.6	-0.01	1.3	3.0	3.0
A(4)	.43 (4.6)	1.1.	-0.00	3.2	7.2	7.2
A(9-16)	.38 (3.8)	.9	0.00	3.7	7.0	7.0
Station						
A(1-4)	.83 (25.9)	38.0	-0.01	20.9	41.1	41.1
A(4)	.52 (5.9)	46.4	0.02	32.7	52.7	52.7
A(9-16)	.82 (13.1)	83.7	-4.36	42.1	73.5	73.6

R(t-value) = correlation coefficient between actual and predicted volumes and its t-value
AE = average error
|AE| = the average absolute error
SD = standard deviation
RMSE = $SD^2 + A^2$ = the root mean square error

$U\text{-}a$ = the utility of an access mode, and
Cov = the percentage of the zone covered by the walk access area.

Statistical tests indicate that the coefficients in both models are significant at .99 level of confidence. Model I was chosen over Model II primarily because of its consistency with the access mode model, or

$$\text{Station choice: } \begin{cases} \text{nearest} & \text{if distance to station} \\ & < \tfrac{1}{2} \text{ mi} \\ P(S|l) & \text{otherwise} \end{cases} \quad (10)$$

Application of the Travel Demand System

Now that the access supply models and the access mode/station choice models have been developed, the travel demand model can be evaluated by applying it in stages with each stage affecting the following stage.

The first stage of the model is the prediction of the values of the supply variables. Parametric models of Table 1 are used to get the mean values for the supply variables to each station serving the zone. The operating cost for the automobile was a function of the distance from the zone centroid to the station.

The second stage of the model is the estimation of the modal splits to each station. Again, it was assumed that everyone living in the zone within a ½-mi radius of the station walks to that station. It was, furthermore, assumed that people walking to the station have chosen their housing premises on the basis of proximity of the rail station. Therefore, people living within walking distance of the station are more likely to ride the rail system than people who must use another access mode. Accordingly, it was assumed that the walkers are 85 percent more likely to use the rail mode than people who must use automobile or bus to reach the station. This value was based on a Skokie Swift mode choice study where a logit coefficient was estimated for a similarly defined variable (*11*).

In the third stage the station selection model was applied. Each station was evaluated on its own merits and compared with the characteristics of competing stations.

The final stage of the system, as applied here, is the computation of the "generalized" access price to line, $U\text{-}l$. As explained, the "logitly" consistent aggregation of modes and stations amounts to computing the expression $\log(\Sigma \exp U\text{-}s|l)$. The information used in computing $U\text{-}l$ can be used to parcel the travel volume by station and access mode.

The recursive model system was applied to each of the three data sets having different zone sizes, and the predicted shares of the access modes and station usage were obtained. Volumes were found by multiplying the predicted shares from the recursive model by the actual total number of station users (known from the STAC report).

Evaluation of Results

Four measures of predictive accuracy are calculated for each of the three data sets A(1-4), A(4), and A(16). The measures are the correlation coefficient (R) between actual and predicted volumes and its t-value, the average error (AE), the average absolute error (|AE|), standard deviation of the error (SD), and the root mean square error (RMSE = $SD^2 + AE^2$). The results are given in Table 3.

The observed and predicted access mode shares are in good agreement for all the modes in all three data sets. However, the walk and automobile models have much better results than the bus. Both walk and automobile have very high correlation coefficients and t-values at each level of aggregation.

The bus mode gave good results for the first data set but deteriorated for the larger zones. After examining the two larger data sets, A(4) and A(16), it was found that the bus volumes were well predicted in the core areas where the bus lines were closer and the service more frequent. However, in the fringes of the study area, some zones that had no bus service, or at least very poor service, were combined with zones having either satisfactory or good bus service. It was these combined zones in the fringe areas that caused the results to be not quite as good as in the other zones. This fact points toward the need for explicit aggregation procedures to maintain high accuracy in forecasts; however, see later comments on other sources of error.

The station choice results are also very good. The first and third data sets, A(1-4) and A(9-16), have high correlation coefficients, whereas the second data set has only average results. However, each of the three correlation coefficients is significantly different from zero with .99 level of confidence. They also have low standard errors.

The examination of other error indicators (AE, |AE|, SD, and RMSE) gives rise to the following observations. First, bus volume errors are low, contrary to what we would expect from the correlation coefficients. Second, prediction errors increase with increasing zone size. This is especially true for the automobile and walk modes, and it is also true for the station choice. It would be easy to declare that either zone sizes must be kept small or that travel forecasts need to include specific aggregation measures if nominal forecasting errors are to be kept reasonable, at least when using large zones. However, such a conclusion is not supportable by these data. There are other hitherto unmentioned sources of error that act precisely in the same direction as zonal aggregation, that is, increasing errors with increasing zone size.

In addition to model error and the lack of aggregation procedures, the most outstanding of the so far unmentioned error sources are the following. First, the percentage of people living within ½ mi of the station, and thus the percentage of people having walk access to the station, was simply approximated by the percentage of the zonal areas that fell within ½ mi of the stations. It is well known that development densities near stations are often higher than further from them; vacant land is also more likely farther from the stations. Better knowledge of the distribution of the residences within traffic zones would definitely have increased the accuracy of the results. Second, in several zones the stations were on competing rail lines, either on the two branches of the Illinois Central or Rock Island Railroads or on the South Shore & South Bend Railroad. Because no model was developed for line choice and because these railroads, particularly the Rock Island RR versus the other two, had distinctly different egress attributes that directly affected line choice and indirectly affected station and access mode choices, one would expect noise in the access mode access station predictions. The Chicago network shows vividly why the inclusion of egress analyses, in exactly the same way as the access analyses in this paper, is necessary for reliable travel forecasts in transportation studies involving rail lines. Third, in many zones express bus service provided by the Suburban Safeway Company competed vigorously for the rail traveler. Even though this is a bus service, its attributes are more in line with the rail service and should definitely be taken into account in complete analyses. Fourth, it must be kept in mind that the model access mode choice was estimated (in part) by using the data generated at the finest aggregation level. Thus, if the model coefficients are "contaminated" by data aggregation, they will perform best at the same level of aggregation. At a minimum it can be said that the demand side model favors the finest level of aggregation. Thus, even though the model system was by necessity applied in an incomplete manner, the results are strikingly good and suggest that it is a useful planning tool. In addition, the results provide indirect evidence that choice of mode to work is closely tied to residential location decisions. This fact, which was observed in the Skokie Swift study cited earlier and the fact that coefficients estimated in that study proved useful in the present study, indicates that the relationship between mode to work and residential location is subject to regularities that can be modeled.

CONCLUSIONS

The study has demonstrated that large zones in conjunction with parametric supply and demand equations can effectively be used in transportation planning. This can speed planning processes and allow for more reliable and quicker prediction of land use activities. Use of large zones also enables review of input data and land use predictions by expert panels, local interest groups, and others having an interest in the planning process and travel predictions.

Parametric supply models can be developed also for interzonal transportation systems (*3*), thus freeing the analyst and the planner from coding the networks, which currently is one of the major roadblocks to analyzing systematically a large number of significantly different alternatives. Parametric supply models also facilitate sensitivity analyses because unit changes in supply can be related in a straightforward manner to both demand and resource costs; (marginal) pollution impacts can also be traced in this manner. The implementation of such a model system would be a major step toward more timely and systematic transportation planning.

There is nothing to prevent increasing the zone size indefinitely. In so doing, however, the parametric supply models must be made an order of magnitude more sophisticated. Such zone-independent supply models would be analogous to properly aggregated behavioral travel demand models. They would relate the values of the supply variables to the transportation system attributes and the distribution of economic activities within the region via the travel demand models. Such a model system would find its most rewarding use in sketch planning and comparing alternative city forms as well as in statewide planning, where the zones must necessarily be very large.

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Travel Demand Forecasting with Dynamic Microsimulation

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A new travel demand forecasting system, based on microanalytic simulation and dynamic analysis, is discussed. The system consists of two components: a microsimulator of household socioeconomics and demographics and a dynamic model system of household car ownership and mobility. Each component comprises interlinked models formulated at the household level. Replicated in the socioeconomic and demographic microsimulator are interactions and causal paths that underlie life cycle evolution of individuals and households. Output from the sociodemographic component is then used by the dynamic model system of mobility to predict household car ownership, trip generation, and modal split. The parameters of the model system have been estimated using observations from five waves of the Dutch National Mobility Panel data, covering the period of 4 years from April 1984 through April 1988. Other sources of information, external to the panel data, were also used to estimate key parameters. The availability of the large-scale panel data has been essential for the development of the detailed demographic and mobility model components. The model system is a credible and flexible forecasting tool with which a wide range of future scenarios can be examined to answer a variety of "what if" questions. Issues related to the model structure, data requirements, estimation methods, assumptions, and forecasting performance are summarized.

In travel demand analysis and forecasting the recognition that time is an indispensable dimension of travel demand models is a recent phenomenon. A new forecasting method that explicitly accounts for the dynamic character of travel demand is described. The approach attempts to combine dynamic models of travel behavior with sociodemographic and economic microanalytic simulation to produce a flexible forecasting tool. The development of the Microanalytic Integrated Demographic Accounting System (MIDAS) is summarized, and its use in forecasting is discussed.

The use of cross-sectional models in travel demand forecasting involves some fundamental problems. First, it is based on the untested assumption that cross-sectionally observed variations in travel behavior can be used as valid indicators of behavioral changes over time. Second, future values of socioeconomic and demographic input variables are obtained using "allocation" methods, which "post-process" aggregate forecasts into "pseudo-disaggregate" data. As such, the methods fail to effectively and accurately capture the internal relationships among the input variables. And third, it does not properly represent response lags involved in long-term mobility decisions (e.g., residence location and car ownership).

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An alternative travel demand forecasting system is presented in this paper. The system consists of two components: a microsimulator of household socioeconomics and demographics and a dynamic model system of household car ownership and mobility. Each component comprises interlinked models formulated at the household level. Replicated in the socioeconomic and demographic microsimulator are interactions and causal paths that underlie life cycle evolution of individuals and households. Simulation units evolve from year to year, experiencing marriages, divorces, births, deaths, and so forth. Employment, income, driver's license holding, education level, and household size and composition are among the variables that are internally generated in the simulation. User-defined parameters have been provided for modification to create any future growth path desired.

The parameters of the model system have been estimated using observations from five waves of the Dutch National Mobility Panel data, covering the period of 4 years from April 1984 through April 1988. Other sources of information, external to the panel data, were also used to estimate key parameters. The availability of the large-scale general purpose panel data has been essential for the development of the detailed demographic and mobility model components.

The model system is a flexible and credible forecasting tool with which a wide range of future scenarios can be examined to answer a variety of "what if" questions. It can replicate reality with accuracy comparable with other forecasting models and represents a new approach to forecasting travel demand. However, the method is complex, poses high demands in model estimation, and requires a large amount of data.

BACKGROUND AND STRUCTURE OF THE MICROSIMULATOR

The large systematic biases and the low predictive accuracy of long-range planning and forecasting motivated the adoption of strategic planning—the identification of preferable transportation policies as input to plan development (*1*). Policy strategies are identified beforehand, scenarios are developed for each strategy, and pertinent forecasts are derived. The strategic planning process requires forecasting tools to provide growth scenarios instead of point estimates. Moreover, forecasting creates the need for several alternative growth scenarios, each based on a different set of assumptions about economic development and demographic evolution.

In transportation the usual techniques are either problem-oriented descriptive analyses or forecasting procedures similar to those of the Urban Transportation Planning Process (UTPP).

The need for a system that can answer "what if" questions, under user-defined circumstances of the real world, is clear. This tool should allow the exploration of policies so that it could be used either as a decision insight system (a system that allows policy analysts to introduce subjective input and observe the output) or as an extrapolatory scenario-based system (a system that provides information about the future based on data and observed relationships from the past). The effort described in this paper is the starting point for the creation of a flexible and comprehensive "test bed" for alternative theories and methods of forecasting travel demand.

Socioeconomic and demographic information plays an important role in the four-stage UTPP procedure requiring input variables such as population, income, employment, and car ownership. These methods are extremely sensitive to the accuracy of the information provided externally. Travel demand models are usually cross-sectional individual- and household-based models, whereas the input to these models (i.e., sociodemographic and land use information) is obtained through approximate disaggregation techniques (*2*).

Whereas the techniques, models, and procedures used to obtain input to UTPP are disparate, they share one common characteristic: they are not at the same level of disaggregation as travel demand models. Most agencies transform regional information to the district level, and then from the district level to the traffic zone level. These allocation methods do not provide all the required information needed by the travel demand models. Additional detailed information is obtained using approximate post-processing procedures (disaggregation procedures). The provision of input at the zone level necessitates the application of travel demand forecasting models designed for households and persons at the traffic zone level, too. As expected, both the conversion of aggregate sociodemographic forecasts to zonal forecasts and the conversion of individual travel demands to zonal demands produce many errors throughout the process. Bajpai (*3*) observed that "techniques to project automobile ownership, household income, and household size from population and employment are highly recommended for future research." Travel demand forecasts based on existing techniques are questionable.

Most of the sociodemographic variables describe and attempt to replicate decisions made by individuals and households, so the need arises for models that predict just such variables at the elementary level of decision making. Aggregate responses to policy changes can be obtained by grouping households and individuals into the specific traffic zones or following any other aggregation scheme desired. This approach can be called a "bottom-up" procedure. It is well known that bottom-up approaches lead to more accurate results.

Microsimulation and Dynamic Analysis

Arrow (*4*) and Orcutt et al. (*5*) have shown that microsimulation is a particularly flexible approach in that it adopts a comprehensive system analysis to explain, predict, and compare the impacts of alternative transport policy strategies. The method enables the forecasting of direct and indirect effects of the simulated policies on the system analyzed. Microsimulation can help fill the gap in forecasting the input to travel demand models and provides the framework for designing a new dynamic forecasting tool. These compelling arguments in favor of microsimulation are examined here in view of the added complexity of the method and the increased data requirements.

When the data at hand are cross-sectional observations, the usual assumption is either that behavior does not change or that the changes are given by cross-sectional variations. Therefore, forecasts of changes over time are either nonexistent or are extrapolations from differences in the cross-sectional sample considered. Davies (*6*) notes that cross-sectional analyses fail to differentiate between age effects and cohort effects, fail to resolve ambiguities in causalities, cannot provide methods to consider observable or unobservable omitted variables, and exaggerate the behavioral effect of policy changes by not being able to incorporate phenomena such as inertial response to change.

One of the most promising research approaches to overcome these weaknesses is dynamic analysis. This is the procedure used to describe changes in behavior occurring over a period of time. Forecasts based on these estimates may prove better than cross-sectionally derived ones because models can be developed from dynamic hypotheses and tested with longitudinal information. Future behavior can be predicted by extrapolating observed changes that are reflected in the dynamic models.

Microsimulation and dynamic models need data for model estimation and the construction of microanalytic scenarios. The best source of data is a panel survey. In panel surveys the same information is collected on the same individuals over a period of time. Questionnaires and travel diaries are distributed at different times to the same individuals to collect detailed sociodemographic and travel data. Panel data enable us to develop models that relate behavioral changes to changes in contributing factors in dynamic context, specifying intertemporal causation properly (*7*).

Structure of the New System

The unique characteristic of the approach followed in this study is the combination of a dynamic model of travel behavior with dynamic microsimulation, which is motivated by the following. Since simulation in general implies modeling of a process that evolves over time, dynamic disaggregate models are the natural ingredient of the simulation. Hence, throughout the design of MIDAS, dynamic models at the level of the household and the household member are used to replicate real world changes in sociodemographic characteristics and mobility.

The forecasting tool is made of two components: the sociodemographic component and the mobility component. The sociodemographic component aims to realistically recreate the progression of a household through life cycle stages and simulate changes in the household members' socioeconomic and demographic attributes, such as employment status and driver's license holding. Then the mobility component uses these endogenously generated socioeconomic attributes to forecast household car ownership and mobility. The two components are integrated to form a comprehensive simulation system.

SOCIOECONOMIC AND DEMOGRAPHIC COMPONENT

In the simulation, a household member will age, form an independent household, gain employment, obtain a driver's license, marry, give birth, and so on. The size and composition of the household will change accordingly. A household member may be added to a household through a marriage, or a household may be split into two through a divorce. A child will leave his parents and form a new household. Such changes are probabilistically generated in the simulation. The model parameters that determine the probability of these events are obtained from the Dutch Panel data set.

Household Type Transition

In MIDAS the transition between household types is viewed as the fundamental element of household evolution representing household life cycle stage. Given a transition in household type, new household members are generated, or existing household members are eliminated, and member characteristics are altered in MIDAS. The transition in household types thus serves in MIDAS as a control that constrains the characteristics of household members.

Five household types are used: single-person households, households of a man-woman couple, nuclear family households, single-parent households, and other households. This classification, which is based on the major conclusion of the activity-based travel analysis that children of a household have an important influence on the travel patterns of its adult members, reflects the notion of life cycle (*8*).

For each household in the simulation, characteristics are first read from an input file comprising records of sample households from the Dutch Mobility Panel data set. Following this, the transition between household types is simulated for each time period (1 year is used as the time interval of the simulation). This process is based on a set of logit models that determine transition probabilities for each household as functions of attributes such as the presence of children by age group and the adult household members' age, education, and employment.

A set of subroutines has been developed to probabilistically change the attributes of household members, generate new members, or remove individuals from the household. For example, two subroutines are called in connection with the transition from family to family, or from single parent to single parent, when the number of children is two or more. Another routine is called in connection with the transition from single to single. It accounts for the possibility that the member of a single-person household passes away, and thus the household vanishes [a description of the routines is given elsewhere (*9*)].

Birth and Death

The probability that a woman in a household will give birth to a child in a given year is expressed as a function of the age and employment status of the woman and the number of children that already exist in the household. Observed frequencies obtained from the Dutch Panel data set are used to determine the probability that a woman in a household will give birth to a child.

A birth may be implied by a change in the household type (e.g., a couple to a family). In such cases, the logit models of household type transitions depict the probability of a birth. For example, the probability of a transition from couple to family is expressed as a function of the man's age and education and the woman's employment status. The event of birth is randomly generated in the simulation using these probabilities.

A single-person household is removed when a death takes place in the simulation. The possibility of death is also considered in connection with the transition from couple (or family) to single (or single parent). If a death does not take place in the simulation, the transition is regarded as a result of a divorce, and the household is split into two households.

Households Formed by Children

The event of "leaving the nest" (i.e., a child moving out and forming an independent household) is modeled as a function of the age, sex, and employment status of the child. Similar to the case of birth, this event is implied by household type transition from family to couple or from single parent to single. The probabilities of these transitions are represented by the logit models as functions of the number of children by age.

When the event of nest-leaving takes place in the simulation, a new household is added to the data file with a certain probability, representing the probability that the new household will remain in the same municipality. The evolution of this new household is simulated through the rest of the simulation period.

Employment and Income Models

The employment status of a person is determined using transition matrices developed by sex and age group. Each matrix contains the probability of change in employment from one status to another. For example, the two-by-two matrix for men in the 18-to-24 age bracket indicates that a person who is employed at Time t will also be employed at Time $t + 1$ with probability 0.929.

Given the employment status, the personal income is determined using a set of dynamic models. The personal income at Time t is assumed to be determined in part by the personal income at Time $t - 1$, called lagged dependent variable. It is also assumed that there is correlation between the unexplained effect of Time $t - 1$ and that of Time t, called serial correlation. The income models are developed for the four possible combinations of the employment status at Time $t - 1$ and Time t: (not employed, not employed), (employed, not employed), (not employed, employed), and (employed, employed).

The personal income of each household member is added in the simulation to obtain total household income. The employment transition matrices and the parameters of the income models are estimated using data obtained in a period of economic expansion (1984 through 1988). These parameters must be adjusted if the model is to be applied for a period of stable economy or economic recession. This adjustment requires examination of the impact of the regional and national economy on the parameters of these model components, which is outside the scope of this study.

Driver's Licenses and Education

The driver's license holding is determined using transition matrices similar to those for employment status. Compared with the transition matrices for employment status, the driver's license matrices in general have larger diagonal elements, which correspond to the transition from licensed to licensed or from nonlicensed to nonlicensed. This implies that license-holding status is less variable than employment status. Also notable is the stability in the transition probabilities across the age groups.

Education is among the explanatory variables used in the MIDAS mobility component, and it is necessary to determine education levels for those household members that are internally generated in the simulation process. This determination is not based on detailed modeling of education levels because it is clearly beyond the scope of this study.

The education levels of children that are generated in the simulation are determined randomly using the distribution of education levels by sex obtained for individuals 18 through 28 years old in the panel data. Education levels of new members that enter a household through a marriage are determined using the correlation between the education levels of married men and women. For example, the probability that a man has a given education level is determined by the education level of the woman who has been a member of the household in the simulation.

New Household Members

A set of personal attributes needs to be generated whenever a new household member is introduced in the simulation. When a new person enters a household through marriage, the person's age and education are determined on the basis of the existing member's age and sex. The new member's employment and income are then determined on the basis of age and sex.

For a newborn member of a household, only sex is determined at the time of birth; other attributes are determined when a person reaches the age of 18, using the probabilities of employment, license holding, and income.

The person attributes of "other" household members are determined as follows. First, the age and sex of the "other" individual are randomly generated on the basis of the age of the head of the household. Employment, license holding, education, and income are then randomly determined on the basis of the observed distribution of the attributes of "other" persons by age and sex.

Household Dissolution

A household is split into two or eliminated from the simulation after a divorce or other events that cause its dissolution. If children are present in the household, they are randomly assigned to the respective parents probabilistically. Only a fraction of newly formed households (formed through divorces or by children gaining independence) remain in the simulation. The value of 15 percent is chosen so that new households roughly replace households that disappear because of death and keep the total number of households in the simulation stable over the simulation years. This process replicates a demographically stable region.

Most model parameters are estimated using subsamples from the Dutch Panel data set. A subsample of Dutch Panel households is also used in the simulation. Observed household and person attributes of 1984, 1985, and 1986 are used as initial conditions; demographic and socioeconomic attributes and mobility levels of these and internally generated new households are simulated year by year to 2010 in MIDAS.

Input Parameters and Modifiers

The parameters in MIDAS can be classified into three categories. The first contains the coefficients of the dynamic models in the mobility component and the income models in the demographic component. These coefficients have been estimated from subsamples of the Dutch Panel data set using econometric methods and have been embedded in the MIDAS programming code. The second category contains 16 sets of parameters of the demographic components. Most represent transition probabilities associated with changes and are treated as input data. Their values have been estimated using the Dutch Panel data set. These parameters can be modified to represent a particular scenario of interest (e.g., an increase in women's labor force participation) or to incorporate external information. The third category is a set of input parameters that can be used for modifications of MIDAS settings. These are modifiers that can be used to change the annual growth of personal income, the birth probabilities, the male and female employment transition probabilities, the male and female license holding transition probabilities, and the household type transition probabilities.

Initial Sample Weighing

MIDAS stimulates the evolution of a subset of those Dutch Panel households that participated in Waves 1, 3, and 5. (The Dutch Panel is made of 10 contacts. The data used in this paper are from Waves 1, 3, 5, 7, 9, and 10, which correspond to March of 1984, 1985, 1986, 1987, 1988, and 1989, respectively. The data of Waves 1, 3, 5, 7, and 9 are used for estimation and the data of Wave 10 for validation.) Many models in MIDAS are dynamic, requiring observations from three time points in the simulation. Because of the initial sampling scheme and attrition, this subset of panel households does not represent the Dutch population. Two sets of weights have been developed for this subsample using available nationwide statistics. The weights are later used to duplicate households by Monte Carlo simulation [the derivation, use, and comparison between alternative weighing schemes are described elsewhere (*2*)].

MOBILITY COMPONENT

The MIDAS mobility component consists of a car ownership model, household motorized-trip generation models, a modal split model, car-trip distance models, and transit-trip distance models. All models are formulated for weekly totals. These mobility measures are obtained from the Dutch Panel survey in which only household members at least 12 years old were requested to report trips, and trips made by individuals less than 12 years of age are not reflected in the measures. Consequently, the MIDAS mobility component does not reflect trips made by individuals less than 12 years old.

Car Ownership Model

An ordered-response probit car ownership model is used to determine household car ownership in MIDAS. This model probabilistically describes the choice of an alternative from among a set of ordered discrete alternatives. A household's choice of the number of cars to own falls in this class of choice. The model assumes the presence of a latent variable that cannot be directly measured but is related to the observed choice—the number of cars owned in this case. Corresponding to a level of car ownership is a range of the latent variable value, which is defined by unknown threshold values. The model is a discrete choice dynamic model with serial correlation and was estimated in a five-stage maximum likelihood method (*10*).

The short-term MIDAS forecasting performance has been tested in a validation exercise. The models in the MIDAS mobility component are used to predict Wave 10 mobility measures using observed explanatory variable values from the Wave 10 data. Predictions thus obtained are then compared with observed measures in the Wave 10 data. The validation effort of this study is based on longitudinal data [i.e., a subset of observational time points (Wave 10 data) is set aside for validation]. If the models replicate Wave 10 observations well, evidence is offered that the models are capable of providing adequate short-term forecasting by replicating the sample closely.

The first part of Table 1 presents the average of five simulation runs. Car ownership levels are correctly forecast for approximately 90 percent of the sample households. The average number of cars per household is predicted to be 0.922, whereas the observed Wave 10 average is 0.945. The error is within 2.5 percent.

Dynamic Motorized-Trip Generation Models

Weekly household motorized-trip generation models, based on data from Waves 1, 3, 5, 7, and 9, have been developed separately for households with cars available and those without a car available. The variables used in the models are the number of diary keepers, number of women, number of men, number of workers, a set of income variables, car ownership, number of drivers, household types, residence area type, and a lagged dependent variable (number of trips a year ago).

Table 1 summarizes the validation results of the motorized-trip generation models. Two models have been formulated, separately for car-owning and carless households. The models are also dynamic with lagged dependent variables and serially correlated errors. Predictions are produced with two different methods: (*a*) using observed Wave 10 car ownership to classify sample households into car-owning and carless households and to exogenously determine the value of a multicar ownership dummy variable in the model for car-owning households; and (*b*) using simulated Wave 10 car ownership levels to classify households. The second method, which more closely represents MIDAS simulation forecasting, is subject to additional errors in household classification.

The results indicate that the models are performing well, in particular the one for car-owning households. The larger errors observed for the model for carless households are presumably due to smaller sample size.

Modal Split Model

Level-of-service data are not available to describe trip characteristics by alternative modes that connect given origin and destination zones. Modal split models that can be developed with this limitation are not trip-interchange (postdistribution) models that focus on modal competition at the disaggregate trip level. A new model structure, binomial logistic (BL), has been defined in this study to predict modal split.

Since land use and transportation network data for the 20 municipalities from which the Dutch Panel sample was initially drawn were not available, the only available measures on the supply side are a rough indicator of transit service level by municipality and accessibility measures by mode based on destination choice models (*11*).

The panel data set contains weekly travel information, which represents many travel mode choices repeated by the same household members. These repeated choices may be collectively explained by accessibility or other macroscopic level-of-service indicators.

Furthermore, mode choice may be made considering not each trip but a series of linked trips to be made as a whole by the individuals. Then the attributes of trips by alternative modes between a given origin and destination pair may not be as influential as one might think. To the contrary, household car ownership, the number of drivers in the household, overall level of transit development, and other sociodemographic attributes may be the major determinants of weekly household modal split. From this viewpoint, the appropriate measure of mode choice is the relative frequency of trips made by a particular mode rather than the mode chosen for each trip. These considerations motivated the new modeling effort reported by Goulias and Kitamura (*12*).

The BL model performed well in terms of data replication. The variables used were the number of diary-keepers in the household, number of cars available, number of drivers, and level of public transit availability. In particular, the results indicate that households without a car available and households in a large urban area with a regional transit district tend to have higher fractions of public transit trips.

The weekly household modal split model is validated similarly through simulation. The analysis here used Wave 10 observed explanatory variable values. The model's performance is evaluated in terms of the fraction of transit trips and the number of transit trips. The Wave 10 observed number of motorized trips is used together with a predicted fraction

TABLE 1 Mobility Component Validation with Wave 10 Observations

Car Ownership Model (five simulation runs)

	Predicted			
Observed	**Zero Cars**	**One Car**	**Two+ Cars**	**Total**
Zero Cars	217	12	0	229
(%)	17.2	0.9	0.0	18.1
One Car	21	816	39	876
(%)	1.7	64.5	3.1	69.2
Two+ Cars	0	59	101	160
(%)	0.0	4.7	8.0	12.6
Total	238	887	140	1265
	18.8	70.1	11.1	100

% of cases correctly classified = 89.7

Weekly Motorized-Trip Generation Models (five simulation runs)

	Car Owners		Non Car Owners	
	(a)	(b)	(a)	(b)
N	1036		229	
Trips Observed	32.1		12.1	
Trips Predicted	32.9	31.2	13.0	13.0
%Error	2.65%	-2.64%	7.51%	7.26%
MAE	9.2	10.6	5.7	5.9
MSE	134.6	182.6	51.1	58.0
R^2	0.725	0.620	0.648	0.597

Weekly Household Modal Split Model (five simulation runs)

	Proportion of Transit Trips	Number of Transit Trips
Observed	0.140	2.9
Pred (1)	0.146	
%Error	4.7%	
Pred (2)	0.134	2.7
% Error	4.5%	8.4%
MAE	0.121	2.9
MSE	0.040	22.7
Correlation	0.637	0.519

Notes: (a) Observed car ownership levels are used as input. (b) Simulated car ownership levels are used as input. MAE = Mean absolute error, average of the absolute difference between observed and estimated value. MSE = Mean square error, average of the squared difference between observed and estimated value. Pred(1) = Average of $(1/(1+\exp(-\beta'x))$ across observations. Pred(2) = Obtained by simulation.

of transit trips to obtain the latter measure. The model is performing well as indicated in Table 1.

In validation, the correlation coefficients between observed and predicted Wave 10 mobility measures are often as good as those obtained during model estimation; the models are not only replicating observed behavior well but also predicting future (i.e., Wave 10) behavior with comparable accuracy. The analysis of this section lends support to the simulation forecasting reported in the next section.

MIDAS LONG-TERM FORECASTING

The evolution of household demographics and socioeconomics, car ownership, and mobility is simulated with MIDAS using the expanded/weighed panel household samples. A simulation period of 25 years is used starting with 1986, when the Wave 5 survey was conducted, and ending in 2010. One year is used as the time increment in the simulation. Therefore, the characteristics of each sample household are updated 25 times in the simulation.

One of the objectives of this study is to examine whether dynamic microsimulation forecasting is practical and meaningful. Manipulation of the MIDAS parameters that have been estimated using the Dutch Panel data is kept to the minimum in this paper. In this section, the results of a baseline MIDAS run—Baseline Scenario—are compared with observed Dutch national mobility statistics (hereafter called the OVG mobility measures), car ownership forecasts by van den Broecke (hereafter called the VDB forecasts), and mobility forecasts by the national model.

The MIDAS baseline forecast represents an income growth of 57 percent by 2010. The results are presented in Table 2 for 1986 (the base year), 1995, 2000, 2005, and 2010. All MIDAS results presented in this section are averages of five simulation runs repeated for each simulation case using different seeds for random number generation.

Comparison with Observed 1986 OVG Mobility Measures

Dutch national mobility statistics (*13*) are used to examine the closeness to the Dutch population of the panel sample used in MIDAS. The results are summarized in Table 3. The survey years are exactly the same (i.e., 1986). The two sets of mobility measures are similar, in particular trip generation measures.

The MIDAS base year trip rates are consistently below the 1986 OVG trip rates. It is believed that the OVG mobility measures are averages over all days of the week, including Saturdays and Sundays. For example, the motorized-trip rate is 0.5 percent below the comparable OVG trip rate. This is a weak indication of underreporting in the Dutch panel survey (*14,15*).

Comparison with the VDB Forecasts

On the basis of a cohort model, van den Broecke produced driver's license holdings and car ownership forecasts for the Netherlands (*16–18*). His forecasts are compared with MIDAS forecasts in Table 3. The driver population and the national car ownership forecasts by VDB are close to the MIDAS forecasts.

Good agreement exists between VDB and MIDAS in the 2010 labor force participation forecasts, which are represented here as the percentage of employed persons in the total population. MIDAS assumes practically the same income growth rate as VDB. Considering the fundamental differences in data and methodology, the compatibility between the VDB forecasts and MIDAS results, including driver's license and car ownership, is striking.

Comparison with the National Model

The Dutch national model provides the only mobility forecasts available to this study (*19,20*). The results are summarized in Table 4 along with MIDAS forecasts. The differences in household size and labor force participation are similar to those seen earlier.

The 2010 driver's license holding in the national model forecasts is practically identical to the forecast by MIDAS. Driver's license holdings are forecast in the national mode using a set of discrete choice models formulated at the household level. Thus the forecast is not a simple extrapolation of observed trends. MIDAS forecasts are based on transition probabilities of license holdings, whereas van den Broecke's forecast relies on license ownership probabilities assumed for

TABLE 2 Baseline MIDAS Forecasts, 1986–2010

	Base Year 1986	MIDAS Forecasts 1995	2000	2005	2010	Growth
Population (x 10^6)	14.5				15.1	4.1%
Population, ≥ 12 Years Old (x 10^6)++	12.3				13.0	5.7%
Household Size	2.64	2.38	2.20	2.06	1.94	-26.5%
Labor Force Participation*	42.7%	49.8%	48.4%	45.0%	41.2%	
Average Income per Employed Person	100	127	134	143	157	
Number of Licensed Drivers (x 10^6)**	7.19				10.04	39.3%
Percent of Licensed Drivers	49.6%	58.2%	61.6%	65.2%	66.5%	
Number of Automobiles (x 10^6)**	4.50				7.10	57.8%
Automobiles per Person	0.31	0.39	0.42	0.45	0.47	51.6%
Automobiles per Household	0.82	0.92	0.92	0.92	0.90	9.8%
Automobiles per Driver	0.62	0.66	0.68	0.69	0.70	12.9%
Number of Motorized Trips per Week						
Per Person	9.35	11.64	12.29	12.91	12.86	37.5%
National Total (x 10^6)**	115.0				167.2	45.4%
Number of Car Trips per Week						
Per Person	8.28	10.38	10.95	11.54	11.47	38.5%
National Total (x 10^6)**	101.8				149.1	46.4%
Number of Transit Trips per Week						
Per Person	1.07	1.27	1.34	1.37	1.39	29.9%
National Total (x 10^6)**	13.2				18.1	37.1%

++Van den Broecke (*16*.)
The 2010 figure was adjusted to agree with the CPB forecast.
*Among individuals of 15 years old and over (CPB), or 18 years old and over (MIDAS).
**MIDAS forecasts are expanded using the national population (of individulas of 12 years old and over for mobility measures).

TABLE 3 Comparison of MIDAS Sample and MIDAS Forecasts with 1986 OVG Observations and VDB Forecasts

	OVG	MIDAS
	1986*	1986
Population (x 10^6)		14.5
Population, ≥ 12 Years Old (x 10^6)++		12.3
Number of Motorized Trips per Week		
Per Person	9.73	9.35
National Total (x 10^6)**		115.0
Number of Car Trips per Week		
Per Person	8.47	8.28
National Total (x 10^6)**		101.8
Number of Transit Trips per Week		
Per Person	1.26	1.07
National Total (x 10^6)**		13.2
Vehicle-Kilometers Driven per Week		
Per Person	114.1	87.5
National Total (x 10^6)**		1076
Transit Passenger-Kilometers Trips per Week		
Per Person	28.7	23.0
National Total (x 10^6)**		283

	VDB[1]		MIDAS	
	1985	2010	1986	2010
Population (x 10^6)			14.5	15.1
Population, ≥ 12 Years Old (x 10^6)++			12.3	13.0
Labor Force Participation[2]	31%	38%	31.5%	38.6%
Average Income per Employed Person	100	170	100	157
Number of Licensed Drivers (x 10^6)**	6.90	9.30	7.19	10.04
Percent of Licensed Drivers in Population	48.0%	61.0%	49.6%	66.5%
Number of Automobiles (x 10^6)**	4.50	7.90	4.50	7.10
Automobiles per Person	0.31	0.52	0.31	0.47
Automobiles per Household			0.82	0.90

*CBS (*13*)
++Van den Broecke (*16*).
The 2010 figure was adjusted to agree with the CPB forecast.
**MIDAS forecasts are expanded using the national population of individulas of 12 years old and over.
[1]Van den Broecke (*17*)
[2]Percentage of employed persons in the total population.

respective population age cohorts. These three entirely different forecasting methods have produced 2010 driver population forecasts that are within 8 percent of each other.

Vehicle-kilometrage growth forecasts of MIDAS and the national model are again strikingly similar. The national model forecasts an increase of 72 percent by 2010. The corresponding MIDAS forecast is an increase of 80.5 percent.

The forecasts of public transit use are drastically different between the two. The national model predicts a slight decrease in public transit passenger-kilometers by 2010, and MIDAS forecasts an increase of 46 percent in car trips and an increase of more than 112 percent in vehicle kilometers. No changes in accessibility and levels-of-service are assumed in either method.

This discrepancy in public transit use between MIDAS and the national model is perhaps the single most important discrepancy. Unfortunately, there is no other comparable forecast available to this study to indicate which forecast is more likely. Both are based on elaborate model systems formulated at the household level. One important difference is that the national model is formulated using cross-sectional data, and longitudinal changes in population compositions are represented by weighting households (as in static microsimulation). MIDAS, on the other hand, is based on longitudinal data and simulates household evolution over time.

CONCLUSIONS

This study, representing an entirely new approach to travel demand forecasting, is based on the recognition that no external demographic and socioeconomic forecasts are furnished at levels that meet the data requirements of sophisticated discrete choice models currently used in transportation planning. Specifically, no external forecasts are produced to provide a multivariate distribution of the array of explanatory variables typically used in travel choice models at the levels where these models are formulated (i.e., households or individuals).

TABLE 4 Comparison of MIDAS Forecasts with National Model Forecasts

	National Model#		MIDAS		
	1986	2010	1986	2010	Growth
Population (x 10^6)	14.3	15.1	14.5	15.1	
Population, ≥ 12 Years Old (x 10^6)++			12.3	13.0	
Household Size	2.70	2.29	2.64	1.94	
Total Workforce (x 10^6)	4.6	6.1			
Labor Force Participation	39.2%	48.5%	42.7%	41.2%	
Number of Licensed Drivers (x 10^6)**	6.6	10.4	7.19	10.04	
Percent of Licensed Drivers	46.2%	68.9%	49.6%	66.5%	
Number of Automobiles (x 10^6)**	4.3	7.9	4.50	7.10	
Automobiles per Person	0.30	0.52	0.31	0.47	
Automobiles per Household	0.81	1.20	0.82	0.90	
Change in Weekday Vehicle-Kilometers[2]	+72%				
Vehicle-Kilometers Driven per Week					
Per Person			87.5	149.4	70.7%
National Total (x 10^6)**			1076	1942	80.5%
Change in Weekday BMT Passenger-Kilometers[2]	-7%				
Change in Weekday Rail Passenger-Kilometers[2]	-2%				
Transit Passenger-Kilometers per Week					
Per Person			23.0	46.3	101.3%
National Total (x 10^6)**			283	602	112.7%

Vrolijk, Gunn and van der Hoorn (*19*), Gunn, van der Hoorn and Daly (*20*)
++Van den Broecke (*16*).
**MIDAS forecasts are expanded using the national population (of individulas of 12 years old and over for mobility measures).
[1]Estimated using the total population and the number of households used in a National Model study.
[2]Read from a graph in (*20*)

The use of dynamic microsimulation is motivated by its flexibility and its ability to forecast direct and indirect effects of the simulated policies on the system analyzed. Microsimulation helped to fill the gap in forecasting the input to travel demand models and provided the framework for designing the new dynamic forecasting tool MIDAS. It generates demographic and socioeconomic, as well as car ownership and mobility forecasts internally through microsimulation. A system of dynamic models estimated using the Dutch National Mobility Panel data set is applied in this simulation.

The primary objective of the study—to determine whether long-range travel demand forecasting can be practically and meaningfully performed using microsimulation with a system of dynamic models and parameters estimated using a panel data set—has been met, along with the secondary objective—to design a flexible tool for building scenarios based on alternative policy strategies. The forecasting exercise reported here is the evidence that a dynamic microsimulator is a credible forecasting model system. In addition, a large number of parameters can be modified by the user to represent scenarios of interest; the microsimulator can automatically simulate the repercussions that follow and reflect them in its mobility forecasts.

Dynamic microsimulation offers many advantages over the traditional cross-sectional models with externally produced sociodemographic variables. However, it is complex and requires a large amount of data. The estimation of a dynamic mobility model requires more data than does a corresponding cross-sectional model. The estimation of dynamic models using panel data requires additional attention because of panel attrition, conditioning, and fatigue.

The dynamic microsimulator described in this paper is the first step toward a full-fledged dynamic microsimulation forecasting system in the transportation planning field. Despite meeting the study objectives, the dynamic microsimulator is not yet a completed tool. Its current version needs to be improved in a number of ways (*2,9*).

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Fixed-Point Approach To Estimating Freeway Origin-Destination Matrices and the Effect of Erroneous Data on Estimate Precision

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A fixed-point approach was applied to the problem of estimating freeway origin-destination (OD) matrices given historical sequences of input and output counts. This estimator was compared with other previously tested estimators in simulation experiments that demonstrated the properties of the chosen estimator and the effect of erroneous data on the precision of the OD estimates. The simulation results indicated that the fixed-point estimator produced the most accurate OD estimates of those tested and that data with measurement error (e.g., from malfunctioning loop detectors) severely affect the precision of OD estimates.

Research on improved methods of control and management of traffic on urban freeways has been gaining increased attention because of growing freeway congestion coupled with limited foreseeable investment in new infrastructure. Attention is now concentrated on efforts to improve the efficiency of existing facilities through better means of freeway surveillance, ramp metering, incident detection, and so forth. To achieve maximum effectiveness in these areas, we need the capability of anticipating traffic problems, such as bottlenecks, before they occur. Therefore, models that produce accurate short-term forecasts of freeway flow are a top priority. Such models usually require an accurate estimate of the freeway origin-destination (OD) matrix. An origin-destination matrix gives the magnitude of travel during a given interval of time from each of the trip origins (on-ramps) to each of the trip destinations (off-ramps). In practice, the true OD matrix is seldom available because the collection of OD data is costly, time consuming, and less accurate than the more easily collected traffic volume data. Consequently, there has been considerable research interest in the development of models or techniques that are capable of estimating freeway OD matrices from input and output counts. Such data are usually collected automatically through loop detectors installed at different sections of the freeway. Since these counts are collected continuously, models that could use these counts to estimate OD patterns could also provide important information on changes in trip patterns over time to traffic and transit planners.

Research in this area of model development can be grouped into two main categories. In the first category (static models), only a single set of input and output counts is used for estimation. The estimation problem here is underdetermined, and a prior OD matrix is required to produce the "updated" estimate. The estimation process involves updating the prior OD matrix in such a way that the updated estimate reproduces the selected set of input and output counts. However, the quality of such updated matrices depends on the quality of the prior estimate, which, in most cases, is poor and difficult to obtain (*1*). Studies in this category of model development include Van Zuylen and Willumsen (*2*), Willumsen (*3*), Van Zuylen (*4*), Nguyen (*5*), Cascetta (*6*), Maher (*7*), Stokes and Morris (*8*), and Hendrickson and McNeil (*9*). In the second category of model development research (dynamic models), historical sequences of input and output counts are considered. The use of time series data here causes these estimation problems to be overdetermined. Studies in this category include Cremer and Keller (*10,11*) and Nihan and Davis (*1,12*). These authors present a number of algorithms that are based on prediction-error minimization methods to estimate movement volumes for a single intersection given time series of entering and exiting counts at each intersection leg. There has been limited success, to date, in extending the application of the second category of models to more complicated networks. This paper addresses the application of such models to a simple freeway network.

Most of the models developed for estimating OD matrices assume the availability of error-free data. However, recent studies by Jacobson et al. (*13*) and Chen and May (*14*) indicate a number of ways in which loop detectors can malfunction and provide erroneous data [e.g., stuck sensors, chatting, pulse breakup, hanging (on or off), and intermittent malfunctioning]. Since our interest lies in estimating the OD matrix parameters from time series of input and output counts and since the estimation assumes conservation of flow in each time period, it is important that the data observed be as error-free as possible. This was the motivation for the second part of our study, which addressed the potential impact of measurement error in resulting OD estimates.

This paper attempts to accomplish two tasks. The first is the development of an estimation technique based on the "fixed-point problem" (FPP) approach that is capable of estimating the freeway OD matrix given time series of input and output counts. The second involves exploration of the effect of measurement error in input and output counts (e.g., due to faulty loop detectors) on the precision of estimates

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and the asymptotic properties of estimators used. The malfunction of loop detectors is simulated by adding a measurement error to traffic counts at selected entry or exit points. Loop detectors in good working condition (reliable traffic counts) are represented as having zero measurement error, whereas malfunctioning loop detectors are simulated by adding a measurement error term to the data.

PROBLEM DESCRIPTION AND MODEL FORMULATION

Problem Description

The objective of this research was the development of an algorithm that could accurately estimate the proportion of flow from each on-ramp to each off-ramp given a section of freeway and time-series of entering (on-ramp) and exiting (off-ramp) counts. Specifically, the objective was the estimation of the OD matrix proportions $b_{ij}(t)$ given time series counts of $\mathbf{q}(t)$ and $\mathbf{y}(t)$ (input and output counts respectively) so that Constraints 1 and 2 are satisfied.

$$\sum_{j=1}^{N} b_{ij}(t) = 1.0 \qquad i = 1, 2, \ldots, M \tag{1}$$

$$b_{ij}(t) \geq 0 \qquad i = 1, 2, \ldots, M \qquad j = 1, 2, \ldots, N \tag{2}$$

where

$b_{ij}(t)$ = the proportion of vehicles originating at i and destined for j at time t,
M = total number of origin points (on-ramps and upstream mainline), and
N = total number of destination points (off-ramps and downstream mainline).

The first two constraints ensure conservation of flow during each time interval and elimination of any negative OD volumes, respectively. A third constraint prohibits flow from an on-ramp to an upstream off-ramp:

$$b_{ij}(t) = 0 \qquad (i, j) \in Z \tag{3}$$

where Z is the set of OD pairs that are known a priori to have zero flow.

Cremer and Keller (*10,11*) showed that the output counts can be expressed as weighted sums of input counts.

$$\mathbf{y}'(t) = \mathbf{q}'(t)\mathbf{B}(t) + \mathbf{e}'(t) \tag{4}$$

$$E[y_j(t)] = \textstyle\sum_i b_{ij} q_i(t) \tag{5}$$

where

$\mathbf{q}(t)$ = $m \times 1$ vector of input counts for time t,
$\mathbf{y}(t)$ = $n \times 1$ vector of output counts for time t,
$\mathbf{B}(t)$ = $m \times n$ matrix with elements $b_{ij}(t)$ = proportion of trips from i to j during time t,
$\mathbf{x}(t)$ = $m \times n$ matrix of OD volumes for time t, and
$\mathbf{e}'(t)$ = transpose of the $n \times 1$ vector of prediction errors (assumed independent and normally distributed).

Although this formulation was developed for intersection models, where the travel time from origin to destination is very short, it was assumed that this could also be applied to the freeway OD problem, provided that the time interval, t, were long enough to accommodate increased travel times. It was further assumed that an interval three or four times longer than the longest OD travel time for the study section would be acceptable. This would allow most trips that originated at some point in the freeway section during that interval to be completed within the same interval. This simple, first-stage assumption avoided the necessity for a more complex formulation including lagged input variables.

Previous Estimation Approaches

Typically, there are two possible approaches to estimating the OD matrix parameters from time series counts: recursive (online) and nonrecursive (off-line). In the nonrecursive approach it is assumed that the $\mathbf{B}(t)$ matrix is time invariant and that the OD parameter estimates apply for the entire period. In the recursive approach, the $\mathbf{B}(t)$ matrix is allowed to vary with time, and a new set of OD estimates is produced for each interval in the time period.

Nonrecursive Estimators

If the OD matrix can be assumed to be time invariant, Equation 4 becomes a standard linear regression equation, and, since the time series counts of inputs and outputs are known, the ordinary least squares (OLS) estimator can be used to estimate the OD matrix. The objective is to choose the $\mathbf{B}(t) = \mathbf{B}$ matrix that minimizes the sum of the squared prediction errors:

$$SS_j = \textstyle\sum_t [y_j(t) - \mathbf{q}'(t)\mathbf{b}_j(t)]^2 \tag{6}$$

A constrained least squares (CLS) approach that ensures that Equations 1 and 2 are satisfied can also be applied in the same manner.

An alternative estimation method, the expectation maximization (EM) algorithm (*15*), has also been applied to the time invariant OD problem. Given that we only observe $q_i(t)$ and $y_j(t)$, the EM algorithm lends itself nicely to this underdetermined problem. For nonrecursive estimators, assuming that the input counts are generated by random variables that are independent across time, the likelihood of the OD movements $[x_{ij}(t) = b_{ij} q_i(t)]$ can be given by

$$L_i \{x_{ij}(t), b_{ij}, i = 1, \ldots, M, j = 1, 2, \ldots, N\}$$
$$= \textstyle\prod_t \{[q_i(t)! / \prod_j x_{ij}(t)!][\prod_j b_{ij} x_{ij}(t)]\} \tag{7}$$

It can be shown that the maximum likelihood estimator of log (L) is

$$\hat{b}_{ij} = \textstyle\sum_t x_{ij}(t) / \sum_t q_i(t) \qquad i = 1, 2, \ldots, M$$
$$j = 1, 2, \ldots, N \tag{8}$$

In an intersection application of the EM approach, Nihan and Davis (*1*) treated the turning movements $x_{ij}(t)$'s as outcomes of multinomial random variables, one for each entering leg. This was under the assumptions that the $\mathbf{B}(t)$ matrix was time invariant, the input counts $q_i(t)$ were known, that each driver arriving at Leg i of the intersection during t made the turning movement decision independently of all other drivers arriving during t, and that all vehicles entering during Interval t also exited during t (conservation of flow). With these assumptions the expected value for each movement from Origin i to Destination j was given by

$$E[x_{ij}(t)] = b_{ij}(t)q_i(t) \tag{9}$$

where $x_{ij}(t)$ is the number of vehicles entering at i and exiting at j during Interval t.

The EM algorithm begins by estimating the conditional expectation of the turning movements $x_{ij}(t)$'s given an initial estimate of the $\mathbf{B}(t)$ matrix and all input and output counts.

$$\textstyle\sum_t \hat{x}_{ij}(t) = \sum_t \{E[x_{ij}(t)] | \mathbf{B}(t), \mathbf{q}(t), \mathbf{y}(t), \quad t = 1, 2, \ldots, T\} \tag{10}$$

The $\mathbf{B}(t)$ matrix is then reestimated by replacing $\Sigma x_{ij}(t)$ in Equation 8 with $\Sigma \hat{x}_{ij}(t)$. The EM algorithm iterates between Equations 8 and 10 until convergence is achieved.

Applied to a four-leg isolated intersection with 100 simulated data sets, the EM estimates of the $\mathbf{B}(t)$ matrix showed much lower variances than a least squares–based estimator. However, these estimates did have significant biases. Moreover, the EM algorithm required high computational demands because both the inverse of the random vector $\mathbf{y}(t)$'s covariance matrix and the covariance matrix between $x_{ij}(t)$ and $\mathbf{y}(t)$ (shown below) had to be calculated at each iteration (*1*).

$$C[y_j(t), y_k(t)] = \begin{cases} -\sum_i b_{ij} b_{ik} q_i(t) & j \neq k \\ \sum_i b_{ij}(1 - b_{ij}) q_i(t) & j = k \end{cases}$$

$$C[x_{ij}(t), y_k(t)] = \begin{cases} -\ b_{ij} b_{ik} q_i(t) & j \neq k \\ b_{ij}(1 - b_{ij}) q_i(t) & j = k \end{cases}$$

Recursive Estimators

Cremer and Keller (*10*) developed an algorithm for dynamic estimation of intersection turning movements. The algorithm could be used to estimate the $\mathbf{B}(t)$ matrix using the recursion equations, which have the form of a stochastic gradient algorithm:

$$b_{ij}(t) = b_{ij}(t-1) + q_i(t)[y_i(t) - \mathbf{q}'(t)\mathbf{b}_j(t-1)] \tag{11}$$

$$\mathbf{b}_j(t) = \mathbf{b}_j(t-1) + (1/t)(\mathbf{R}^{-1})[y_j(t) - \mathbf{q}'(t)\mathbf{b}_j(t-1) \tag{12}$$

$$\mathbf{R}(t) = \mathbf{R}(t-1) + (1/t)[\mathbf{q}(t)\mathbf{q}'(t) - \mathbf{R}(t-1)] \tag{13}$$

Other dynamic approaches considered by Cremer and Keller (*10*) and Nihan and Davis (*1*) include recursive least squares (RLS), which is basically the application of OLS to sequential least squares equations, and normalized recursive least squares (RLSN), which includes the satisfaction of Constraints 1 and 2.

Preliminary Test Using Nonrecursive Estimators with Freeway Data

To date, the preceding approaches have seen limited application and have been primarily used in estimation of turning movements for isolated intersections. When used to estimate the $\mathbf{B}(t) = \mathbf{B}$ matrix of an isolated intersection, the OLS and CLS methods gave consistent, unbiased estimates and low computational demands (*1*). This inspired us to adopt the standard linear regression model as a starting point for estimating the $\mathbf{B}$ matrix of a freeway section.

Figure 1 shows a schematic representation of a section of Interstate 5 in north Seattle. The section consists of six origins (O1–O6) and three destinations (D1–D3). A data set for this section (one time series count for each point of input and output) was obtained from Traffic Systems Management Center of the Washington State Department of Transportation. These counts were automatically collected through loop detectors installed on the freeway. To account for traffic congestion and travel times from origins to destinations, the data were aggregated to 15-min counts for 24 hr, thus giving a time series length of 96.

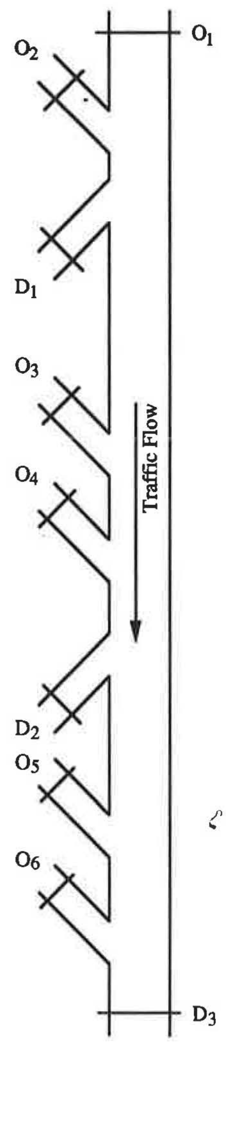

FIGURE 1 Section of Interstate 5 in north Seattle.

Table 1 gives the estimates of the $\mathbf{B}(t) = \mathbf{B}$ matrix using both OLS and CLS. Although the actual **B** matrix is not known, it is clear that OLS failed to produce reasonable estimates (both Constraints 1 and 2 were violated). The estimates produced by CLS satisfy Constraints 1 and 2 but are not realistic. For example, they suggest that about 45 percent of traffic that originates from On-Ramp 2 is destined to Off-Ramp 1 and the rest (55 percent) is destined to Off-Ramp 2. Examination of actual data indicated that conservation of flow was never achieved at most time periods, an obvious indication of loop detector error. This warranted conducting simulation scenarios to investigate the effect of erroneous data on the precision of estimates for the various estimators. Before conducting these simulation scenarios, an additional estimator based on the FPP was developed and included in subsequent evaluations.

Fixed-Point Estimation Approach

As discussed earlier, the EM algorithm was successfully used (*1*) on an isolated four-leg intersection to estimate turning movements. However, the algorithm required high computational demands. Furthermore, to operationalize this algorithm for the intersection problem, all U turns were prohibited to avoid having a singular covariance matrix of the random vector $\mathbf{y}(t)$ [since $\Sigma_i q_i(t) = \Sigma_j y_j(t)$]. To operationalize the EM algorithm to estimate the OD matrix of a given freeway section, one needs to prohibit at least one OD movement (e.g., O_4 to D_2). This is realistic since on-off movements of such short distances are expected to be rare.

To simplify calculations, the estimation problem was structured in such a way that each cell of the OD matrix could be estimated separately. This means replacing both the covariance matrix of the random vector $\mathbf{y}(t)$ by its variance $\{\Sigma_i b_{ij}(1 - b_{ij})q_i(t)\}$ and the covariance matrix of $x_{ij}(t)$ and $\mathbf{y}(t)$ by its variance $\{b_{ij}(1 - b_{ij})q_i(t)\}$. The conditional expectation of the turning movements $\{x_{ij}(t)\text{'s}\}$ are then given by

TABLE 1 Performance of OLS and CLS Estimators on Actual Freeway Data

Movement	OLS bij	CLS bij
11	0.028	0.014
12	0.090	0.005
13	0.695	0.977
21	0.387	0.446
22	0.567	0.551
23	-0.162	0.000
32	-0.045	0.000
33	0.957	1.001
42	-0.723	0.000
43	2.366	1.002
53	3.022	1.001
63	1.056	1.004

$$E\{x_{ij}(t)|\mathbf{B}, \mathbf{q}(t), y_j(t)\} = b_{ij}q_i(t) + C\{x_{ij}(t), y_j(t)\} \times \text{Var}^{-1}\{y_j(t)\}\{y_j(t) - \textstyle\sum_i b_{ij}q_i(t)\} \quad (14)$$

where

$$C\{x_{ij}(t), y_j(t)\} = \{b_{ij}(1 - b_{ij})q_i(t)\} \text{ and}$$
$$\text{Var}\{y_j(t)\} = \textstyle\sum_i b_{ij}(1 - b_{ij})q_i(t)$$

Equation 14 becomes

$$E\{x_{ij}(t)|\mathbf{B}, \mathbf{q}(t), y_j(t)\} = b_{ij}q_i(t) + \{b_{ij}(1 - b_{ij})q_i(t)\} \times \{\textstyle\sum_i b_{ij}(1 - b_{ij})q_i(t)\}^{-1}\{y_j(t) - \textstyle\sum_i b_{ij}q_i(t)\} \quad (15)$$

Summing over t,

$$E[\textstyle\sum_t x_{ij}(t)|\mathbf{B}, \mathbf{q}(t), y_i(t)] = b_{ij}\textstyle\sum_t q_i(t) + \textstyle\sum_t\{b_{ij}(1 - b_{ij})q_i(t)\{y_j(t) - \textstyle\sum_i b_{ij}q_i(t)\} \div \textstyle\sum_i b_{ij}(1 - b_{ij})q_i(t)\} \quad (16)$$

Having structured the estimation problem in such a way that each cell in the $\mathbf{B}(t)$ matrix was estimated separately, it was decided to treat each function as an FPP (*16,17*). This essentially involves solving for the convergence point of a recursive estimation algorithm of the form $b_{ij}^{k+1} = g(b_{ij}^k)$ (i.e., the point where $b_{ij}^{k+1} = b_{ij}^k$. Given $f(b_{ij})$ where $0 \leq b_{ij} \leq 1$, the objective is to find values s such that $f(s) = 0$. Let $g(b_{ij})$ be an auxiliary function such that $s = g(s)$ wherever $f(s) = 0$. The problem of finding s such that $s = g(s)$ is known as the FPP, and s is said to be a fixed point of $g(b_{ij})$. Thus, finding a fixed point for $g(b_{ij})$, $0 \leq b_{ij} \leq 1$, means finding a zero of $f(b_{ij})$, $0 \leq b_{ij} \leq 1$.

From equations 8 and 16, we can represent the recursive function as

$$b_{ij}(k + 1) = \textstyle\sum_t x_{ij}(t)/\textstyle\sum_t q_i(t) = b_{ij}(k) + d/\textstyle\sum_t q_i(t) \quad (17)$$

where

$$d = \textstyle\sum_t\{b_{ij}(1 - b_{ij})q_i(t)[y_j(t) - \textstyle\sum_i b_{ij}q_i(t)]/\textstyle\sum_i b_{ij}(1 - b_{ij})q_i(t)\}$$

Defining

$$f(b_{ij}) = \textstyle\sum_t\{b_{ij}(1 - b_{ij})q_i(t)[y_j(t) - \textstyle\sum_i b_{ij}q_i(t)]/\textstyle\sum_i b_{ij}(1 - b_{ij})q_i(t)\}$$

form $s = g(s)$ reduces to

$$\textstyle\sum_t\{b_{ij}(1 - b_{ij})q_i(t)[y_j(t) - b_{ij}q_i(t)] \div \textstyle\sum_i b_{ij}(1 - b_{ij})q_i(t)\} = 0 \quad (18)$$

Thus, the problem is reduced to solution of a set of n nonlinear equations in n variables. A NAG routine C05NCF (*18*) that uses a modification of the Powell hybrid iterative method is used to obtain a numerical solution, thereby giving the $\mathbf{B}(t)$ estimates.

ALGORITHM TESTING

In this section we investigate the accuracy of the estimators for freeway OD problems and the effect of detector malfunction on the precision of the OD estimates and the properties of the estimators chosen. In addition to the newly developed estimator (FPP), other estimators already developed are considered. Cremer and Keller (*10*) and Nihan and Davis (*1*) present a family of estimators based on the principle of prediction-error minimization that are also included. Thus, in this paper the following estimators are evaluated:

1. OLS,
2. CLS,
3. FPP,
4. RLS, and
5. RLSN.

Since these models require time series data of entering and exiting counts, it is important that the loop detectors provide us with accurate measurement of traffic counts. To investigate the effect of measurement error on the estimates of the $\mathbf{B}(t)$ matrix, we consider two scenarios. The first deals with the case of no measurement error (i.e., no faulty or malfunctioning loop detectors at entry or exit points). In the second scenario measurement error is introduced in both the input and the output counts.

Scenario 1

To test the properties of the algorithms with no measurement error in input or output counts, 50 simulated data sets were generated. Each data set consisted of five simulated days, for 480 time periods. For the selected section shown in Figure 1, input counts (O1–O6) with a counting interval of 15 min were generated for 24 hr, giving six time series of length 96, one for each origin. An OD matrix was assumed as part of the process to simulate the exiting counts. This simulated matrix was taken as the "true" OD matrix. The OD volumes (x_{ij}'s) were generated by the IMSL subroutine GGMTN (IMSL) and summed to produce simulated exiting counts $y_j(t)$. Hence, each simulated day consisted of the same entering counts but different exiting counts. The difference between the total inputs and total outputs for each time period was zero (i.e., conservation of flow was attained).

The FPP estimator was then applied using two simulated entering $[q_i(t)]$ and exiting $y_j(t)$ counts to produce estimates of the true OD values. Table 2 gives the averages of the OD estimates and the standard deviations determined across 50 simulated data sets. These results indicate that the FPP estimator, in general, produced lower variances than did the least squares–based estimators. Furthermore, the estimates were generally unbiased and similar to those produced by OLS, CLS, and RLS. Examining the averages of the $\mathbf{B}(t)$ matrix across 50 simulated data sets, we see that all estimators satisfied Constraints 1 and 2. Table 3 shows the absolute

TABLE 3 Percent Absolute Difference Between $\hat{b}_{ij}$ and True b_{ij} for Scenario 1 (No Measurement Error)

Movement	OLS	CLS	FPP	RLS	RLSN
11	0.10	0.10	0.10	0.10	8.10
12	0.80	1.00	0.70	0.80	9.50
13	0.25	0.11	0.15	0.25	2.20
21	1.20	1.20	0.40	1.20	19.4
22	7.60	8.80	7.20	7.60	29.00
23	0.60	0.60	0.60	0.60	0.60
32	10.90	11.90	10.00	10.90	133.00
33	1.56	1.32	1.44	1.56	14.79
42	1.25	2.40	1.40	1.25	48.35
43	1.00	0.60	0.75	1.00	12.09
53	0.20	0.00	0.00	0.20	0.00
63	0.30	0.00	0.00	0.30	0.00

TABLE 2 Performance of Five Estimators on Simulated Data (No Measurement Error)

Movement	True b_{ij}	OLS $\hat{b}_{ij}$	OLS s_{ij}	CLS $\hat{b}_{ij}$	CLS s_{ij}	FPP $\hat{b}_{ij}$	FPP s_{ij}	RLS $\hat{b}_{ij}$	RLS s_{ij}	RLSN $\hat{b}_{ij}$	RLSN s_{ij}
11	0.100	0.0999	0.0028	0.0999	0.0028	0.0999	0.0025	0.0999	0.0028	0.0919	0.0083*
12	0.100	0.1008	0.00414	0.1010	0.0042*	0.1007	0.0037	0.1008	0.00414	0.0905	0.0042*
13	0.800	0.798	0.0061*	0.7991	0.0049	0.7988	0.0050*	0.798	0.0061*	0.8176	0.0077*
21	0.050	0.0506	0.0101	0.0506	0.0102	0.0502	0.009	0.0506	0.0101	0.0597	0.0053*
22	0.050	0.0538	0.0112*	0.0544	0.0121*	0.0536	0.0103*	0.0538	0.0112*	0.0355	0.0098*
23	0.900	0.895	0.0164*	0.895	0.0145*	0.8950	0.0140*	0.8953	0.0164*	0.905	0.0146*
32	0.100	0.0891	0.0408*	0.0881	0.0422*	0.0900	0.039*	0.0891	0.0408*	0.233	0.0374*
33	0.900	0.914	0.0543*	0.9119	0.0421*	0.913	0.0496*	0.9141	0.0543*	0.7669	0.0374*
42	0.200	0.1975	0.0268	0.1952	0.0286	0.1972	0.024	0.1975	0.0268	0.2967	0.0301*
43	0.800	0.808	0.0469	0.8048	0.0287	0.8060	0.0345	0.8080	0.0469	0.7033	0.0301*
53	1.000	1.002	0.059	1.000	0.000	1.000	0.000	1.002	0.059	1.000	0.0000
63	1.000	0.997	0.020	1.000	0.000	1.000	0.000	0.9973	0.0200	1.000	0.0000

Results of Scenario 1. Averages (b_{ij}) and standard deviations (s_{ij}) for offline estimators.

*Significant difference (0.05 level) between b_{ij} and true b_{ij}.

percentage difference between b_{ij} and the true b_{ij} for each movement. In general, the FPP estimator showed lower differences compared with the least squares–based estimators. The normalized recursive least squares estimators produced the highest differences. Figures 2 and 3 show that both the recursive least squares and the normalized recursive least squares estimators were asymptotically unbiased. However, RLSN had a slower convergence than the RLS. This was to be expected, since the constraints had to be satisfied each time period. Figures 4 and 5 show that both the RLS and RLSN were asymptotically consistent since the variances approached zero. Again the RLSN had slower convergence.

Scenario 2

In this scenario, measurement error was added to selected entry and exit counts. It was assumed that the loop detectors at Origins 1 and 3 and Destinations 1 and 3 (see Figure 1) were malfunctioning. The measurement error at each entry and exit point was generated separately by an IMSL subroutine GGNML, such that the variance of the measurement error at Origin 1 and Exit 3 was set to be 1.5 times the mean of the input counts, whereas the variance at Origin 3 and Exit 1 was designed to be equal to the mean of the input counts. With the introduction of measurement error, the conservation of flow was no longer satisfied at each time period (i.e., the difference between the total inputs and total outputs at each time period was not zero). Table 4 gives the averages of the OD estimates and the standard deviations determined across all data sets. The results indicate that all estimators produced biased estimates. The FPP estimator, however, gave the lowest variances compared with other estimators. Furthermore, the unconstrained estimators (OLS, RLS, and FPP) produced estimates that did not satisfy Constraints 1 and 2. Figures 6 and 7 show the effect of measurement error on the asymptomatic properties of RLS and RLSN. Although RLSN had slower convergence to the true value, it did not have a persistent bias as did the RLS. In terms of consistency, Figures 8 and 9 show that both estimators RLS and RLSN had slow convergence to zero compared with the case of no measurement error (Figures 4 and 5). However, the RLS estimator showed faster convergence to zero than did the RLS (at least for movement b_{13}). Although CLS provided the smallest sum of the absolute difference ($\Sigma|b_{ij} - b_{ij}|$), it produced very large percentage differences, particularly for Movements 22, 32, and 42. Table 5 gives the absolute percentage difference ($|\hat{b}_{ij} - b_{ij}|/b_{ij}$) between the estimated and true OD parameters. The FPP estimator produced the second-lowest sum of absolute difference and generally the smallest percentage difference.

CONCLUDING REMARKS

In addressing the problem of estimating freeway OD matrices from sets of input/output counts, several estimators were tested. The fixed-point estimator developed in this paper showed generally lower variances and more accurate estimates compared with four least squares–based estimators. The paper

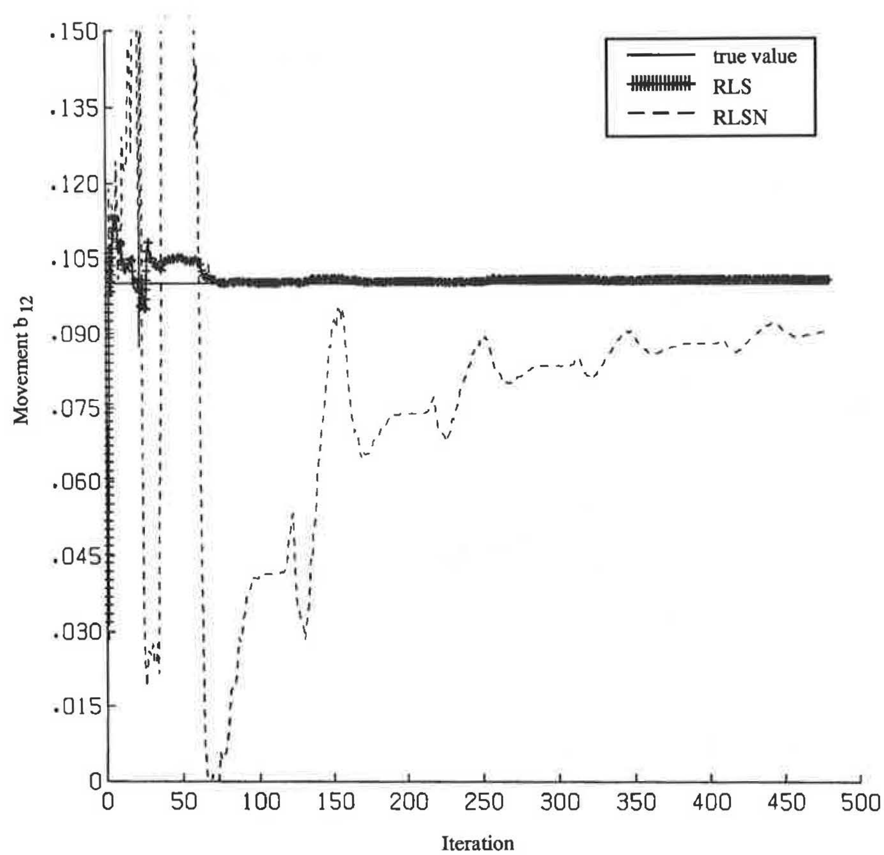

FIGURE 2 Average across simulations of Movement b_{12} computed by two recursive estimators for Scenario 1.

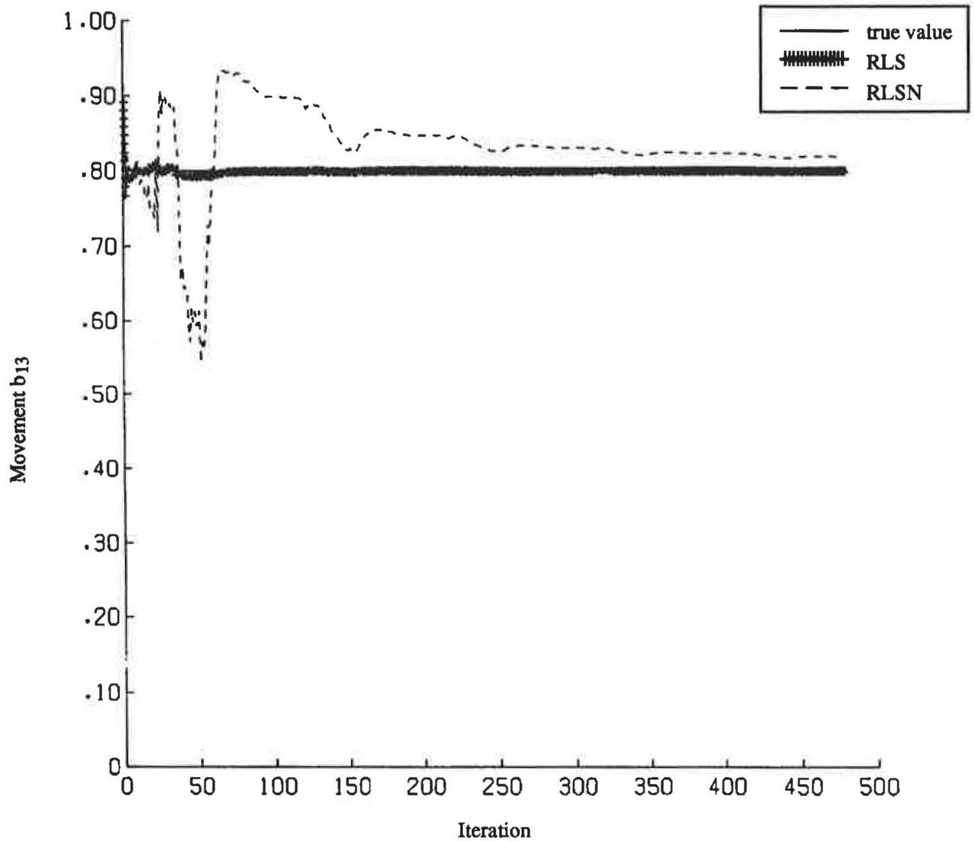

FIGURE 3 Average across simulations of Movement b_{13} computed by two recursive estimators for Scenario 1.

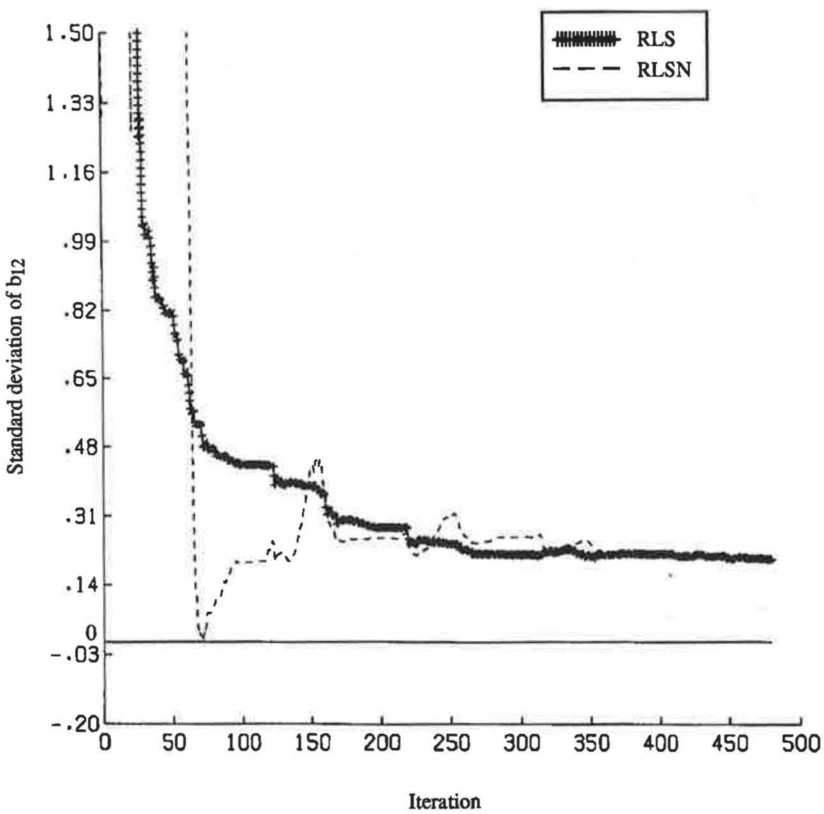

FIGURE 4 Standard deviation across simulations for estimates of Movement b_{12} for Scenario 1.

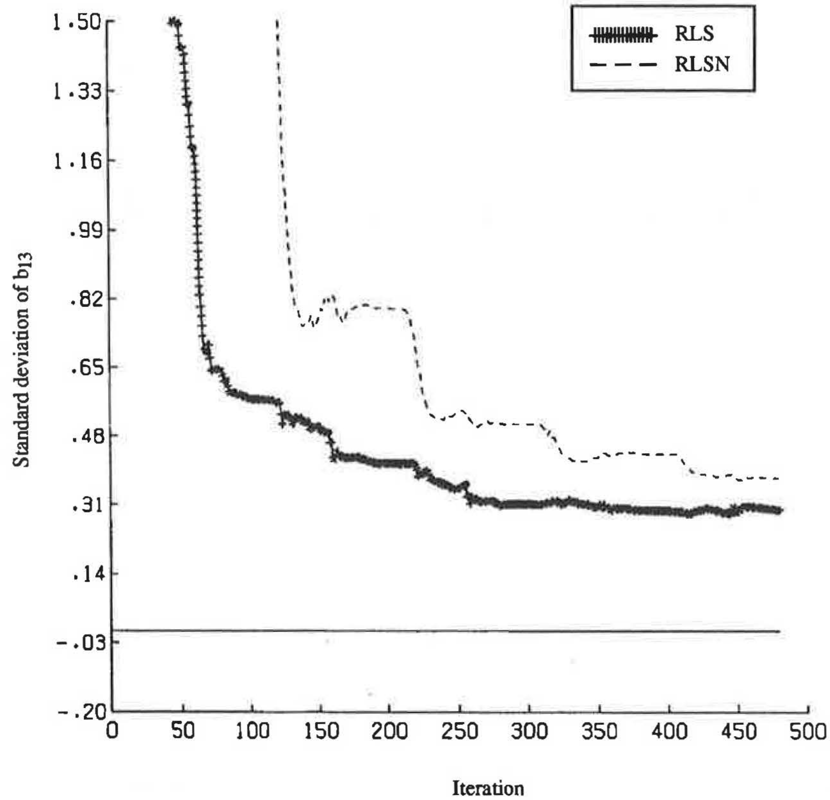

FIGURE 5 Standard deviation across simulations for estimates of Movement b_{13} for Scenario 1.

TABLE 4 Performance of Five Estimators on Simulated Data with Measurement Error at Entry Points 1 and 3 and Exit Points 1 and 3

		OLS		CLS		FPP		RLS		RLSN	
Movement	True b_{ij}	$\hat{b}_{ij}$	s_{ij}	$\hat{b}_{ij}$	s_{ij}	$\hat{b}_{ij}$	s_{ij}	$\hat{b}_{ij}$	s_{ij}	b_{ij}	s_{ij}
11	0.100	0.099	0.0027*	0.105	0.004*	0.098	0.0026*	0.099	0.0027*	0.101	0.015*
12	0.100	0.097	0.004*	0.105	0.008*	0.096	0.003*	0.097	0.004*	0.089	0.005*
13	0.800	0.769	0.022*	0.787	0.012*	0.773	0.018*	0.769	0.022*	0.810	0.014*
21	0.050	0.055	0.009*	0.032	0.013*	0.058	0.009*	0.055	0.009*	0.051	0.017
22	0.050	0.056	0.013*	0.031	0.023*	0.056	0.0102*	0.056	0.013*	0.035	0.019*
23	0.900	0.981	0.055*	0.940	0.031*	0.967	0.052*	0.981	0.055*	0.914	0.022*
32	0.100	0.088	0.038*	0.170	0.086*	0.091	0.030*	0.088	0.038*	0.278	0.108*
33	0.900	0.744	0.191*	0.831	0.086*	0.760	0.162*	0.900	0.191*	0.722	0.108*
42	0.200	0.228	0.032*	0.122	0.063*	0.231	0.027*	0.228	0.032*	0.297	0.063*
43	0.800	0.884	0.165*	0.878	0.064*	1.005	0.129*	0.884	0.165*	0.703	0.063*
53	1.000	1.250	0.261*	1.000	0.001	1.000	0.000	1.250	0.261*	1.000	0.0000
63	1.000	0.993	0.059*	1.000	0.003	1.000	0.000	0.993	0.059	1.000	0.0000

Results of Scenario 2. Averages (b_{ij}) and standard deviations (s_{ij}) for offline estimators.

*Significant difference (0.05 level) between $\hat{b}_{ij}$ and true b_{ij}.

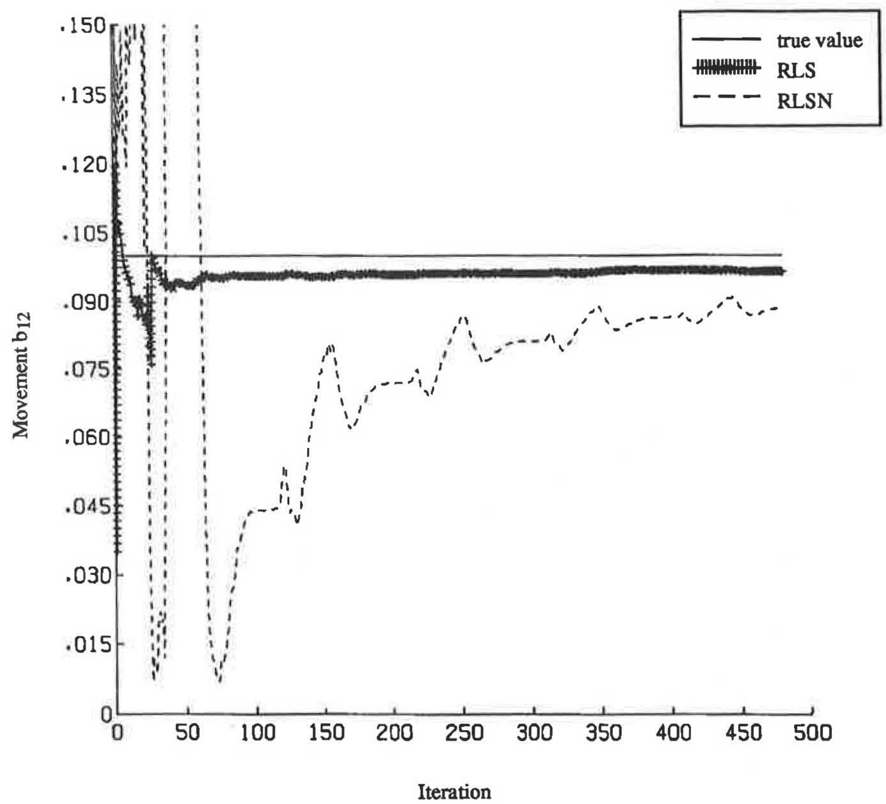

FIGURE 6 Average across simulations of Movement b_{12} computed by two recursive estimators for Scenario 2.

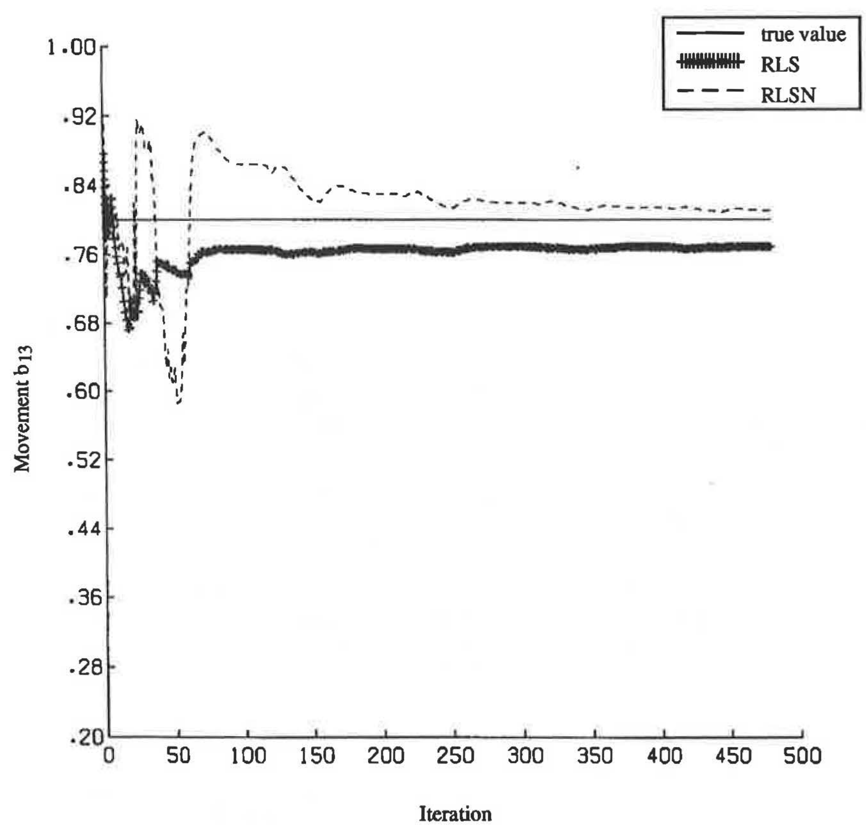

FIGURE 7 Average across simulations of Movement b_{13} computed by two recursive estimators for Scenario 2.

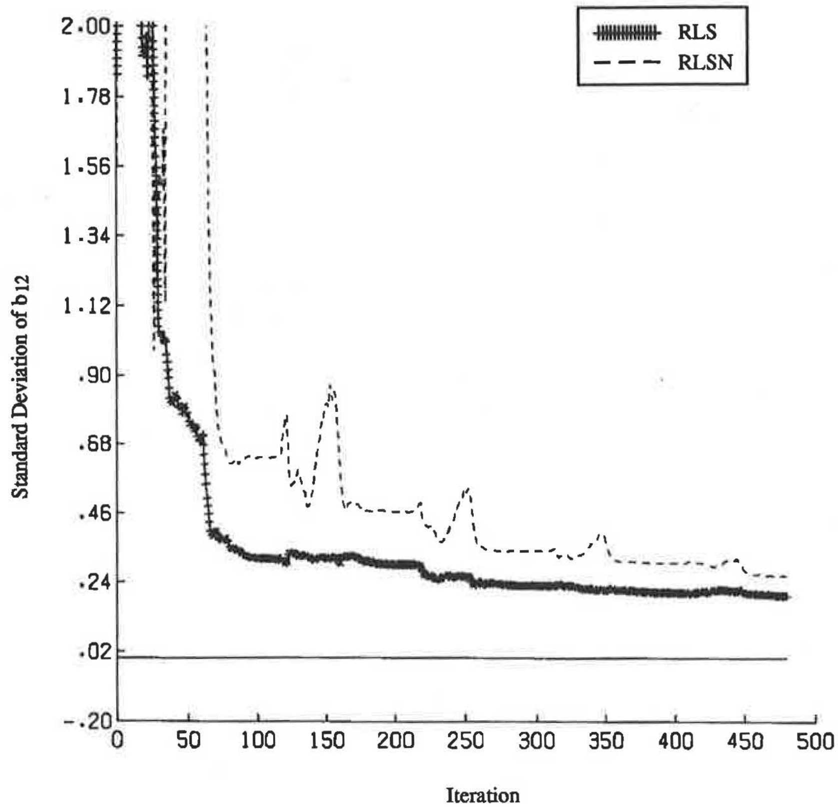

FIGURE 8 Standard deviation across simulations for estimates of Movement b_{12} for Scenario 2.

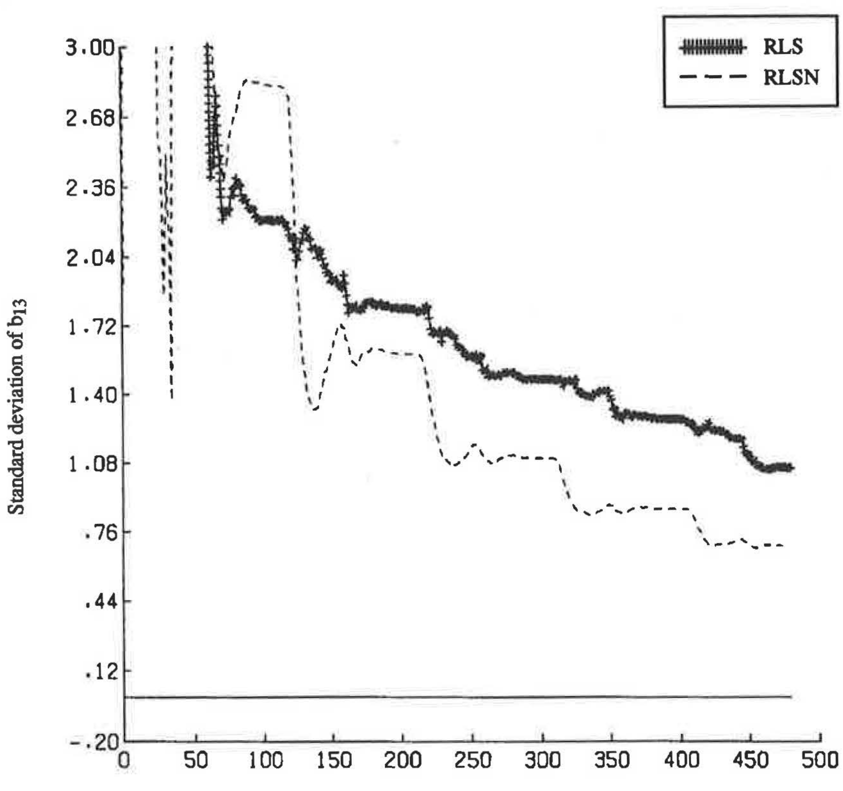

FIGURE 9 Standard deviation across simulations for estimates of Movement b_{13} for Scenario 2.

TABLE 5 Percent Absolute Difference Between $\hat{b}_{ij}$ and True b_{ij} for Scenario 2

Movement	OLS	CLS	FPP	RLS	RLSN
11	1.20	4.50	1.90	1.20	1.20
12	3.50	5.00	4.40	3.50	11.40
13	3.90	1.60	3.40	3.90	1.30
21	9.80	35.60	16.00	9.80	1.60
22	12.40	37.80	12.40	12.40	29.80
23	9.00	4.40	7.40	9.00	1.60
32	12.00	69.60	8.80	12.00	17.80
33	17.30	7.70	15.60	17.30	19.80
42	14.00	39.0	15.50	14.00	48.50
43	10.50	9.80	26.60	10.50	12.20
53	25.00	0.00	0.00	25.00	0.00
63	0.70	0.20	0.00	0.70	0.00

also investigated the effect of erroneous data on the precision of the estimates and the properties of the estimators used by considering two scenarios. The first scenario represented loop detectors that produce accurate traffic counts; in the second scenario, selected entry and exit points were chosen as having faulty or malfunctioning loop detectors. Results indicated that measurement errors severely influenced the precision of OD matrix parameter estimates (percentage errors were significantly increased; Constraints 1 and 2 were no longer satisfied) and the asymptotic properties of these estimators. For example, the RLS became persistently biased when measurement error was introduced. Although these preliminary results are based on simulated scenarios, they highlight the need for theoretical models that account for erroneous data.

With present loop detector technology, erroneous traffic volume counts can be expected from time to time. As illustrated here, the presence of erroneous data severely affects the precision of OD matrix estimates. Therefore, to obtain reasonable estimates, estimators must be capable of handling data with measurement error. Another alternative would be the use of technology that does not inherit the same problems as loop detectors do. Research in this area is active in the United States and Europe. One other alternative currently pursued at different institutions is the detection and diagnosing of erroneous data from loop detectors (*13,14*) before use in forecasting models.

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Traffic Forecasting in the Helsinki Metropolitan Area Transportation Study 1988

MATTI PURSULA AND HEIKKI KANNER

The models developed for traffic forecasting in the Helsinki Metropolitan Area, Finland, are presented. The basic traffic surveys for the Helsinki Metropolitan Area Transportation Study 1988 were done during 1987 and 1988. The main field studies were an origin-destination (OD) survey of automobile traffic, an OD survey of public transport, and a personal trip diary interview. Modeling of only internal trips made by inhabitants of the metropolitan area is described. The modeling was based on the trip diary interview. The model structure was basically a four-step model with feedback between the last three steps. Trip generation was calculated using production and attraction rates. Mode and destination choice were mostly modeled using nested logit models. In network loading, a standard multipath equilibrium assignment model (EMME/2 system) was used. Trips were divided into four categories according to trip purpose (home-based work trips, home-based school trips, other home-based trips, and non-home-based trips). Four alternative modes were included in the mode choice models. The population was divided into categories according to the different steps of the modeling. The most important categorization was the division according to a person's access to a car. Destination choice models included 117 alternative destinations. The coefficients of mode choice models were logical and the variables predictable. The first destination choice models had some theoretical deficiencies, which were partly abolished using constrained estimation. The model system with unconstrained models produced satisfactory forecasts. New models will be estimated and new forecasts will be made during 1992.

The study area, the Helsinki metropolitan area, consists of four cities: Helsinki (485,000 inhabitants), Espoo (165,000 inhabitants), Vantaa (150,000 inhabitants), and Kauniainen (8,000 inhabitants). The city center of Helsinki is located on a peninsula in the Gulf of Finland, and the metropolitan area forms a half circle around it with a radius of 25 to 30 km (total area 1031 km^2, land area 742 km^2). In the city center there are about 118,000 workplaces and 59,000 inhabitants. The number of jobs in the whole metropolitan area is about 442,000.

The car density in the area is about 320 cars per 1,000 inhabitants, and 60 percent of all households have at least one car. The public transport system of the area consists of bus and tram traffic, commuter and ordinary trains, and one subway line east of the city center. Of the 2 million internal daily trips of the inhabitants of the area, 46 percent are made by car, 32 percent by public transport, and 22 percent by bicycle or on foot.

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Buses dominate in public transport. Three-fourths of all public transport trips are made by bus. The share of public transport has been falling continuously during the last 20 years as a result of growing car density.

BASIC TRAFFIC SURVEYS

The basic traffic surveys for the Helsinki Metropolitan Area Transportation Study 1988 (LITU 88) were done during 1987 and 1988. The main field studies were an origin-destination (OD) survey of automobile traffic (*1*), an OD survey of public transport (*2*), and a personal trip diary interview (*3*).

The OD survey of automobile traffic was done at 122 sites on 10 cordon lines that divided the study area into 15 subareas. At each site a mail-back questionnaire was given to 10 to 20 percent of the drivers of the passing automobiles (except buses) between 6 a.m. and 8 p.m. The information asked included OD data, trip purpose, and number of passengers in the car. The drivers were also asked to draw the route of their trip on a map included in the questionnaire. The number of returned and approved questionnaires was about 86,000 (37 percent).

The OD survey of public transport was done by interviewing every fourth boarding passenger in every fourth bus, tram, and train (i.e., 6.25 percent of passengers). The questionnaire was short, and most of the passengers completed it during their trip and returned it directly to the interviewer. Only a small number were returned by post. The most important information in the questionnaire was OD data and information about the number of transfers needed during the trip in question. The number of accepted returned questionnaires was about 56,000, which is 5.6 percent of the 1 million boardings per day in the metropolitan area.

The trip diary interview was person based. The main reasons for the use of this technique were the easiness in sample formation and expansion and the good experience in some recent travel surveys in Finland (*4*).

The objective of the interview was to gather daily travel data plus socioeconomic and other background information from 7,000 inhabitants of the metropolitan area. Only persons 7 years of age or older were included in the original random sample, which was about 2.5 percent (18,000 persons) of the corresponding population. About 66 percent of these had a telephone.

The data were gathered by an informed telephone interview. This means that the questionnaire plus travel diary were sent in advance to people with a telephone (11,900), and after the survey date the person in question was phoned and the data were typed directly into computer memory. The number of accepted telephone interviews was about 6,100, and about 600 accepted answers were collected by mail to represent those persons who had no telephone or could not be reached by telephone.

The trip diary interview study formed the basis for the traffic modeling. In this work the other studies were used mainly for comparison and validation.

In all these surveys three basic zone systems were used. The data were gathered in a very detailed zone division with 282 zones. The models and forecasts were made in a division with 117 zones. For aggregation purposes a division with 19 zones was mainly used.

TRAFFIC MODEL SYSTEM

In this paper only the modeling of the internal trips of the inhabitants of the metropolitan area is described (*5*). These trips are about 90 percent of all person trips in the area, and the modeling is based on the trip diary interview. The modeling of external trips and commercial traffic was done with simple methods and is not discussed here.

The model structure is basically a four-step model with feedback between the last three steps. Trip generation is calculated using production and attraction rates. Mode and destination choice are mostly modeled using nested logit models. In network loading a standard multipath equilibrium assignment model (EMME/2) is used.

Trips are divided into four categories according to their purpose: home-based work trips (33 percent), home-based school trips (11 percent), other home-based trips (42 percent), and non-home-based trips (14 percent). In mode choice modeling there are four alternative modes: walk (and bicycle), car (driver or passenger), bus (and street car), and rail (train and subway). The access trips to rail are made on foot or by bus. Less than 2 percent of rail passengers use park-and-ride, and this mode is not included in the model.

The share of non-home-based trips in the data is low. There are two main reasons for this. The first is that, in the trip diary survey, short (less than 5 min travel time) non-home-based pedestrian and bicycle trips were purposely left out. The second is that non-home-based pedestrian and bicycle trips are not included in the models. The original share of non-home-based trips in the data is 19 percent. This is the same as in the corresponding survey in 1976 with no exclusion of short trips (*6*). In the latest nationwide study, the share of non-home-based trips is about 25 percent (*4*), and in a recent study in Oulu, a middle-sized Finnish city, it is about 33 percent (*7*).

The population is divided into different categories in different steps of modeling. The most important categorization is the division according to a person's access to a car. Persons with a driving license who, according to their own statements, practically always have access to a car for traveling belong to the category HAP (a Finnish acronym for persons who mainly use cars for traveling). Other people belong to the category EHAP (person who usually cannot use car for traveling). About 46 percent of people aged 18 years or more belong to the category HAP. This is clearly more than one person per car registered in the area.

Table 1 gives the main structure of the modeling system. The HAP/EHAP grouping is used in two trip-purpose categories: other home-based trips and non-home-based trips. Some minor categorizations of the population that are used during the modeling are not given in the table. The most important of these are the age grouping and the grouping of the people as working or nonworking (see, for example, Table 2).

TRIP GENERATION MODELS

The production and attraction rates are based on cross-classification analysis of the survey data. The division of the population into detailed categories is hard to forecast, so the trip production rates used in the traffic forecasts and given in Table 2 are based on very few categories.

The generation-attraction principle cannot be applied to non-home-based trips. The production rates given for this trip category in Table 2 were used only to check the total number of non-home-based trips in the metropolitan area. The actual trip locations for non-home-based trips were based on the number of inhabitants and jobs in the zones. The same principle was used for all the attraction rates calculated in the study.

The home-based school trips of persons aged 18 years or more are included in other home-based trips, and they are about 8.5 percent of all trips in this category. In this way the school trip category becomes homogeneous. For example, more than 75 percent of these trips are made on foot or by bicycle.

No trip matrix balancing was done in the study. The attraction rates were used mainly for validation and evaluation for the forecasts in a later phase of the process. They were also used in the calculation of the size variable in some of the destination choice models.

LOGIT MODELS FOR MODE AND DESTINATION CHOICE

Estimation of the Models

Nested logit models were used for mode and destination choice estimation for other home-based and non-home-based trips. The mode choice of home-based work trips was estimated with a logit model as well as the destination choice of the home-based school trips.

The destination choice of home-based work trips was modeled using a housing and workplace matrix from the population censuses. This matrix gives the location of the home and workplace of every working person in the area. The work trips of the present situation were simply distributed using this matrix. The matrix was transformed for future situations with growth factors based on a gravity model analogy. The approximation method is rough and is not discussed further here.

The mode choice of home-based school trips was based on the length of the trip. This could be done because walking

TABLE 1 Structure of the Modeling System of Internal Trips in LITU 88

Trip purpose	Trip generation rates		Mode choice	Destination choice
	Production	Attraction		
Home-based work trips	Trips/working person/day	Trips/employee/day	Logit model	Housing and working place matrix
Home-based school trips	Trips/school-aged person/day	Trips/inhabitant/day	Distance matrix	Logit model
Other home-based trips, HAP-persons*	Trips/HAP-person/day	Trips/inhabitant/day Trips/employee/day	Logit model	Nested logit model
Other home-based trips, EHAP-persons*	Trips/EHAP-person/day	Trips/inhabitant/day, Trips/employee/day	Logit model	Nested logit model
Non-home-based trips**, HAP-persons	Trips/HAP-person/day	Trips/inhabitant/day, Trips/employee/day	Logit model	Nested logit model
Non-home-based trips**, EHAP-persons	Trips/EHAP-person/day	Trips/inhabitant/day, Trips/employee/day	Logit model	Nested logit model

* HAP-person is a person that practically always has access to car for personal trips. Other persons are EHAP-persons.

** Walk (and bicycle) trips are excluded from this trip category.

and bicycling are so dominant in this trip category without direct access to a car. The mode and destination choice of school trips is not discussed further in the paper.

In other home-based and non-home-based trip categories, the nested logit models were estimated separately for HAP and EHAP persons. A stepwise estimation procedure was used (i.e., the mode choice model was estimated first, and the logsum term of that model was used as a variable in the estimation of the destination choice model). Simultaneous estimation was not possible in the original model work because of computer program restrictions.

The estimation of the destination choice models was done using all 117 zones of the metropolitan area as alternatives. At first, estimation using samples with 31 zones per alternative was tried just as in the corresponding study in 1976 (*6*). The results were poor, so the full choice set was used. The reason for the poor results with destination sampling was probably a bias in the methodology. The models were estimated according to the rules of random sampling even though the strategy used was basically a stratified importance sampling described, for example, by Ben-Akiva and Lerman (*8*). Random sampling strategy and the stability of the coefficients will be studied during 1992.

For each trip category where logit models were used for mode choice, two sets of models were estimated. The base models are detailed and include a larger number of variables

TABLE 2 Trip Production Rates (Trips/Person/Day) Used in Traffic Forecasts in LITU 88

Trip purpose	Population group	Trip production rate
Home-based work trips	Working persons, age 18-64 years	1.43
	Other population	0.03
Home-based school trips*	Age 7-17 years	1.77
	Other population	0.00
Other home-based trips**	Age 7-17 years	1.20
	EHAP-persons, age 18-	1.10
	HAP-persons	1.46
Nonhome-based trips***	Age 7-17 years	0.12
	EHAP-persons, age 18-	0.27
	HAP-persons	0.67

* The school trips of persons aged 18 years or more belong to the trip category other home-based trips.

** HAP-person is a person that practically always has access to a car for personal trips. Others are EHAP-persons.

*** Walk (and bicycle) trips are excluded from this trip category.

than the forecasting models that need less data and are used in the aggregate travel forecasts. The focus of this paper is in the forecasting models. Only one example of the base models is given here (Table 3).

Variables and Coefficients of Mode Choice Models

Table 3 gives the variables and coefficients of the mode choice models for home-based work trips. These models were estimated without categorization by access to a car (HAP/EHAP grouping).

The distance for walk trips is given in kilometers. This distance is for a one-way trip between home and work. The travel times, travel costs, and number of transfers in motorized traffic are calculated for a round-trip. Travel times are given in minutes, costs in FIM ($1 U.S. is about 4.3 FIM), and household income in thousands of FIM per month.

The total travel time includes walking, waiting, and in-vehicle times. These are calculated from the traffic networks with the EMME/2 program. For rail users a special procedure is used to give all these components.

Travel costs for public transport are based on the ticket type of the passenger. Travel costs for car (0.46 FIM/km) are out-of-pocket costs (*9*). For home-based work trips the travel costs of a car do not include parking costs. They are calculated in the parking index, which is a linear combination of parking costs and the logarithmic ratio of parking demand to parking capacity.

The base model in Table 3 has more variables than the forecasting model. For example, the possibility of a personally addressed parking place at the workplace and the possibility of a company car are included in the model. A special variable to describe the length of the access to rail stations is also used.

The model coefficients are logical, and the variables in the forecasting model are predictable. If an assumption of constant cost/income relationship is made, then no forecast is needed for these variables.

The value of travel time calculated from the forecasting model in Table 3 with a mean household income of 12,000 FIM/month is about 6.90 FIM/hr. This is about half of the price that was used in cost-benefit analyses by the Finnish National Road Administration in 1988 (*9*). From the base model the value of travel time for components of the work

TABLE 3 Variables and Coefficients of the Logit Models for Mode Choice of Home-Based Work Trips in LITU 88

Variable	Forecasting model Coefficient	t	Base model Coefficient	t	Modes
Ln(distance)	3.601	36.3			Walk
Total travel time	-0.02154	-9.0			Bus, car, rail
Trip cost/income	-2.236	-29.9			Bus, car, rail
Number of transfers	-0.5170	-14.7			Bus, rail
Cars/household	0.7896	5.1	-1.101	-5.6	Car/Bus,rail*
Parking index	-1.010	-4.9	-1.000	-5.7	Car
Walk-dummy	1.873	13.8	-0.7411	-3.9	Walk
Rail-dummy	0.3200	4.9	0.7837	4.7	Rail
Car-dummy	-1.420	-9.6	-3.300	-18.5	Car
Distance 0-10 km **			-0.8838	-28.2	Walk
Distance 10- km **			-0.1639	-4.8	Walk
Access walk time			-0.03476	-7.7	Bus, car, rail
In-vehicle time			-0.01338	-3.9	Bus, car, rail
Cost			-0.2468	-29.4	Bus, car, rail
Number of transfers bus			-0.6980	-12.9	Bus
Number of transfers rail			-0.4229	-9.9	Rail
Sex (female=0, male=1)			1.615	18.8	Car
Waiting time			-0.04733	-6.2	Bus, rail
Access time/road distance			-0.2781	-5.7	Rail
Reserved parking			0.9888	8.3	Car
Company car			1.293	11.4	Car
Number of observations = 4780	ρ^2 = 0.360		n = 4780	ρ^2 = 0.471	
Percent of correct predictions	66.6			72.8	

* The variable cars/household is used for car mode in the forecasting model and for bus and rail modes in the base model.

** If the distance <= 10 km then 'Distance 0-10' equals the distance and 'Distance 10 -' equals zero . If the distance > 10 km then 'Distance 0-10' equals 10 and 'Distance 10-' equals (distance-10).

trip can also be calculated: walk time 8.45 FIM/hr, waiting time 11.50 FIM/hr, and in-vehicle time 3.25 FIM/hr. The ratio of the component values is approximately 2.5:3.5:1. This is in reasonably good accordance with the international findings of traffic model studies (*10*).

Table 4 gives the models estimated for the HAP and EHAP populations for other home-based trips. In this trip category the model structure and most of the variables are the same as in the model for home-based work trips. The values of the variables are for round-trips except walking distance, which is given as a sum of one or two one-way distance variables in the same way as in the base model for home-based work trips. The parking costs are this time included in the cost/income variable. The parking conditions of the destination zone are

TABLE 4 Variables and Coefficients of the Logit Models for Mode Choice of Other Home-Based Trips in LITU 88

	HAP-population *		EHAP-population *		
Variable	Coefficient	t	Coefficient	t	Modes
Distance, 0-5 km **	-0.7838	-13.0			Walk
Distance, 5-10 km **	-0.5489	-7.6			Walk
Distance, 0-10 km ***			-0.7599	-29.6	Walk
Total travel time	-0.01943	-4.0	-0.01643	-6.2	Bus, car, rail
Cost/income	-0.7593	-8.4			Bus, car, rail
Number of transfers	-0.1875	-2.4	-0.4205	-10.0	Bus, rail
Ln(parking ratio-5)	-0.4376	-9.5	-0.3885	-9.2	Car
Acc. time/road dist.	-0.4418	-3.8			Rail
Walk-dummy	1.961	8.1	1.950	17.7	Walk
Rail-dummy	0.7967	2.8	-0.01898	-0.2	Rail
Car-dummy	1.660	9.8	-1.253	-12.7	Car
Number of observations = 2542		ρ^2 = 0.515	n = 4050	ρ^2 = 0.267	
Percent of correct predictions		77.0		60.8	

* HAP-person is a person that practically always has access to a car for personal trips. Others are EHAP-persons.

** If the distance <= 5 km then 'Distance 0-5' equals the distance and 'Distance 5-10' equals zero . If the distance > 5 km and <=10 km then 'Distance 0-5' equals 5 and 'Distance 5-10' equals (distance-5). If the distance > 10 km 'Distance 0-5' equals 5 and 'Distance 5-10' equals 5.

*** If the distance <= 10 km then 'Distance 0-10' equals the distance. If the distance > 10 km then 'Distance 0-10' equals 10.

described with the logarithmic parking ratio variable (demand/capacity).

The access time per road distance variable is calculated as the sum of the access times to and from rail stations divided by the direct road distance between origin and destination of the trip. The variable is a measure of difficulty in the use of a low-density rail network.

The value of travel time can be calculated only for main users of cars (the HAP population) because travel cost is not included in the EHAP models. The value of the time for 12,000 FIM/month income is 18.40 FIM/hr. This is clearly higher than the value for the whole population for home-based work trips.

Table 5 gives the coefficients of the mode choice models for non-home-based trips. Walk and bicycle trips are not included in this trip category, and one-way trips are used in the models. The parking demand variable, though, is a sum of the corresponding variables of both ends of the trip. In this way, parking costs and constraints of both ends of the trip affect the mode choice.

The value of travel time for non-home-based trips can be calculated for both population categories. The value for the HAP population (11.90 FIM/hr) is lower than that for the EHAP population (26.10 FIM/hr). The reason for this surprising result might be the exclusion of the walk trips from the estimation sample. Another reason might be in the differences of the purpose distribution of the non-home-based trips of the HAP and EHAP populations. HAP people clearly make more non-home-based trips than EHAP people, so it is possible that a bigger share of their trips are leisure trips (with a lower time value) than is the case for EHAP people.

The use of rail as a separate mode caused some problems in model estimation. In most models, the share of correctly predicted choices was lowest for rail. The problem was that

TABLE 5 Variables and Coefficients of the Logit Model for Mode Choice of Non-Home-Based Trips in LITU 88

	HAP-population *		EHAP-population *		
Variable	Coefficient	t	Coefficient	t	Modes
Total travel time	-0.05479	-3.2	-0.06058	-4.4	Bus, car, rail
Cost/income	-3.307	-8.0	-1.668	-5.1	Bus, car, rail
Number of transfers	-0.5439	-2.0	-0.2826	-1.4	Bus, rail
ΣLn(parking ratio-5)	-0.2102	-3.1	-0.2113	-3.3	Car
Rail-dummy	-0.3284	-1.4	-0.4938	-3.2	Rail
Car-dummy	1.767	5.1	-1.072	-4.0	Car
Number of observations = 1284		ρ^2 = 0.671	n = 652	ρ^2 = 0.199	
Percent correct predictions		89.1		40.9	

* HAP-person is a person that practically always has access to a car for personal trips. Others are EHAP-persons.

there were no good variables to differentiate between bus and rail. Some attempts were made with nested mode choice models, but the results were not any better. Because of the important role of some new rail construction proposals in the future, rail was kept as a separate mode in the models.

The ρ^2 values of the models are sometimes very high. This is especially the case in models for the HAP population. The reason for this is that the modal split in this population group is very one-sided: three-fourths or more of trips are made by car. A better indicator for the goodness-of-fit of the models would be a revised ρ^2 value that indicates the result in comparison with a model with alternative specific constants only. Unfortunately, the estimation program did not give these values, and they were not calculated afterwards.

Some estimates of model accuracy were done by sample enumeration. The results indicated that the estimates of car and bus shares are mostly quite good (average error mostly only a few percent). The results for rail are clearly worse, especially for HAP persons. This may be an implication of an IIA violation in the model structure for this population category. In practice the difference is not so serious, because HAP persons seldom use rail or any public transport alternative.

Variables and Coefficients of Destination Choice Models

Destination choice models for other home-based and non-home-based trips were estimated separately for HAP and EHAP populations. The models are nested logit models with feedback to mode choice models via the logsum variable. According to theory, the coefficient of the logsum variable should be greater than or equal to zero and less than or equal to one (*8*). If the coefficient is greater than one, some of the cross elasticities in the model can be illogical (*10*).

In some estimating programs it is possible to restrict the coefficient of the logsum variable to 1, but this was not in the program that was originally used during this work. Unfortunately, this led to coefficients that were clearly more than 1, as can be seen from the following tables where the model coefficients are given. After this occurred, a new program with the ability to restrict estimated parameters was used (*11*). In the following, results of unrestricted and restricted estimation are given, but so far no forecasts with the restricted models have been made.

In destination choice models, the attraction is described with a scale variable. Usually this variable contains a linear combination of the amount of different activities in the zone. The scale variable should be in logarithmic form, and its coefficient should be equal to 1 to give a model that is independent of the zone division (*8,10*).

The original estimation of the models of LITU 88 was done without restriction the coefficient of the scale variable to equal 1. Most coefficients turned out to be reasonable (i.e., they did not differ too much from one and were all less than 1). Trials of restricted estimation indicated only minor changes in other coefficients of the models, so these results are not given here.

The weighting of different activities inside the scale variable can also be problematic. The original estimation program that was used in this work could not estimate these weights simultaneously with other model coefficients. For this reason the weights were found partly by trial-and-error and partly by the use of usual attraction rates. With the new estimation program, these weights can be directly estimated. Some of the results are given here. The results indicate that the other coefficients of the model are not very sensitive to the weights.

With the new estimation program it is also possible to estimate the nested logit model for mode and destination choice simultaneously. This estimation makes better use of the data, and a new estimation of the models is going on. In this paper all models are based on sequential estimation of mode and destination choice.

Table 6 gives the results of model estimation for other home-based trips. The corresponding results for non-home-based trips are given in Table 7.

All the destination choice models given above have one to three alternative specific dummy variables. The city dummy is used if the destination of the trip is inside the city center area. Subcenters 1 and 2 refer to the main centers of Espoo and Vantaa. Subcenter 3 is the biggest subcenter inside the borders of Helsinki.

The models estimated with the new program without restrictions included the estimation of the weights in the scale variable, too. The exact results are not given here, but the values of the weights did not differ much from the corresponding values of the restricted estimation given in Tables 6 and 7. The model coefficients were also very near the coefficients of the free estimation of the models. This is natural because the coefficient of the scale variable in free estimation did not differ so much from 1.

The weighted values of the scale variable are clearly of different magnitude in the free trial-and-error estimation and in the new restricted estimation even though the coefficients of the logscale variables are very near each other. The explanation for this is in the nature of logarithmic variables. If a logarithmic variable in a logit model is common to all alternatives, a multiplication or division by constant inside the logarithm has no effect on the coefficient of this or any other variable in the model.

As was mentioned before, all the destination choice models were estimated using all 117 zones as possible choices. The great amount of possible choices results in low ρ^2 values. The basic test used for the goodness-of-fit of the destination choice models was their ability to replicate the trip length distributions of the travel data. An example is given in Figure 1.

The fit of the computed trip length distribution in Figure 1 is far from excellent (observed mean 7.78 km; forecast mean 6.24 km), and the model has to be developed further. It is possible that the simultaneous restricted estimation process that is going on at present will give better results.

TABLE 6 Variables and Coefficients of the Logit Model for Destination Choice of Other Home-Based Trips in LITU 88

Variable	HAP-population *				EHAP-population *			
	Coefficient	t	Coefficient	t	Coefficient	t	Coefficient	t
	(free) **		(restricted)		(free)		(restricted)	
Logsum	1.770	56.5	1.000	0.0	1.830	99.6	1.000	0.0
Logscale	0.7416	24.3	0.7992	21.7	0.9554	29.7	0.9158	34.3
Employment density	0.2629	8.3	0.1787	5.4	0.3022	22.3	0.1058	4.5
City-dummy	0.5908	6.5	0.2805	3.2				
Subcenters1&2-dummy	0.7699	9.0	0.9622	11.2				
Subcenter3-dummy	1.457	12.6	1.501	11.9	1.945	21.4	1.435	15.5
	ρ^2 = 0.189		ρ^2 = 0.180		ρ^2 = 0.338		ρ^2 = 0.288	
Variables in the logscale-variable								
Inhabitants	1.75	-	1.000	0.0	0.55	-	1.000	0.0
Retail employment	52.75	-	2.306	9.7	0.40	-	2.248	19.0
Service employment	24.00	-	0.8768	4.2	0.55	-	-	-
Industrial employment	1.00	-	-	-	0.10	-	-	-
Other jobs	15.50	-	0.2773	0.6	0.10	-	-	-

* HAP-person is a person that practically always has access to a car for personal trips. Others are EHAP-persons.

** Free : free estimation of the coefficient of the logsum variable

Restricted : the coefficient of the logsum variable was restricted equal 1.0

TABLE 7 Variables and Coefficients of the Logit Model for Destination Choice of Non-Home-Based Trips in LITU 88

	HAP-population *				EHAP-population *			
Variable	Coefficient (free) **	t	Coefficient (restricted)	t	Coefficient (free)	t	Coefficient (restricted)	t
Logsum	1.380	36.2	1.000	0.0	1.656	23.3	1.000	0.0
Logscale	0.7578	21.2	0.8593	16.3	0.7289	13.9	1.007	12.4
City-dummy	0.7717	8.8	0.5144	5.8	0.2716	2.5	0.1670	1.4
Subcenter1&2-dummy	0.4343	3.3	0.5144	3.8	0.7803	4.2	0.7307	3.9
Subcenter3-dummy	1.104	6.4	0.9700	5.4	1.328	5.4	1.374	5.2
	$\rho^2 = 0.216$		$\rho^2 = 0.208$		$\rho^2 = 0.256$		$\rho^2 = 0.246$	
Variables in the logscale-variable								
Inhabitants	1.00	-	1.000	0.0	1.00	-	1.000	0.0
Retail employment	57.00	-	3.356	8.2	43.00	-	2.554	6.4
Service employment	32.00	-	1.495	4.2	24.00	-	1.156	3.5
Industrial employment	8.50	-	1.630	5.3	5.00	-	-	-
Other jobs	20.50	-	1.317	2.5	18.00	-	0.5949	1.0

* HAP-person is a person that practically always has access to a car for personal trips. Others are EHAP-persons.

** Free : free estimation of the coefficient of the logsum variable

Restricted : the coefficient of the logsum variable was restricted equal 1.0

Fortunately, the case given in Figure 1 is the worst one. For example, the mean value of the observed trip lengths for home-based work trips is 9.96 km, and the forecast value is 9.62 km. For other home-based trips the values are 7.02 km (observed) and 7.28 km (forecast). For non-home-based trips the values are 7.78 and 6.24 km. This indicates that the models for non-home-based trips have to be developed further.

OTHER MODELS

The forecasting process used in LITU 88 needs some additional traffic models. The most interesting of these are the car ownership models and the model for HAP/EHAP division of the population. For both purposes logit models were used.

Table 8 gives an example of car ownership models. These models are, unlike the other logit models of the study, household based. According to the model, the size of the household has a strong impact on car ownership as well as the type of housing.

In Table 9 there is an example of the HAP/EHAP model. A better model can be estimated if the sex of the person is included. However, the model in Table 9 was used for forecasting because it was assumed that the difference in access to cars between males and females will diminish in the future.

DISCUSSION OF RESULTS

The model system was used to produce basic traffic forecasts for the present situation (as a part of the model validation) and for two future situations. The basic forecasts give the daily trip matrixes divided by trip purpose and mode. The forecasting was done separately for morning and evening peak periods and for the rest of the day. This way, the differences in trip purpose and destination choice during different times of day were taken into account.

The forecasting was based on aggregate data. The zonal means of the variables included in the models were used for all individuals of the zone. This of course is a source of aggregation error, and this must be kept in mind when total results are referred to in the following discussion.

Comparison of the forecast for the present situation with the results of the traffic studies is the final test of the modeling system. The model estimation cannot be based solely on the

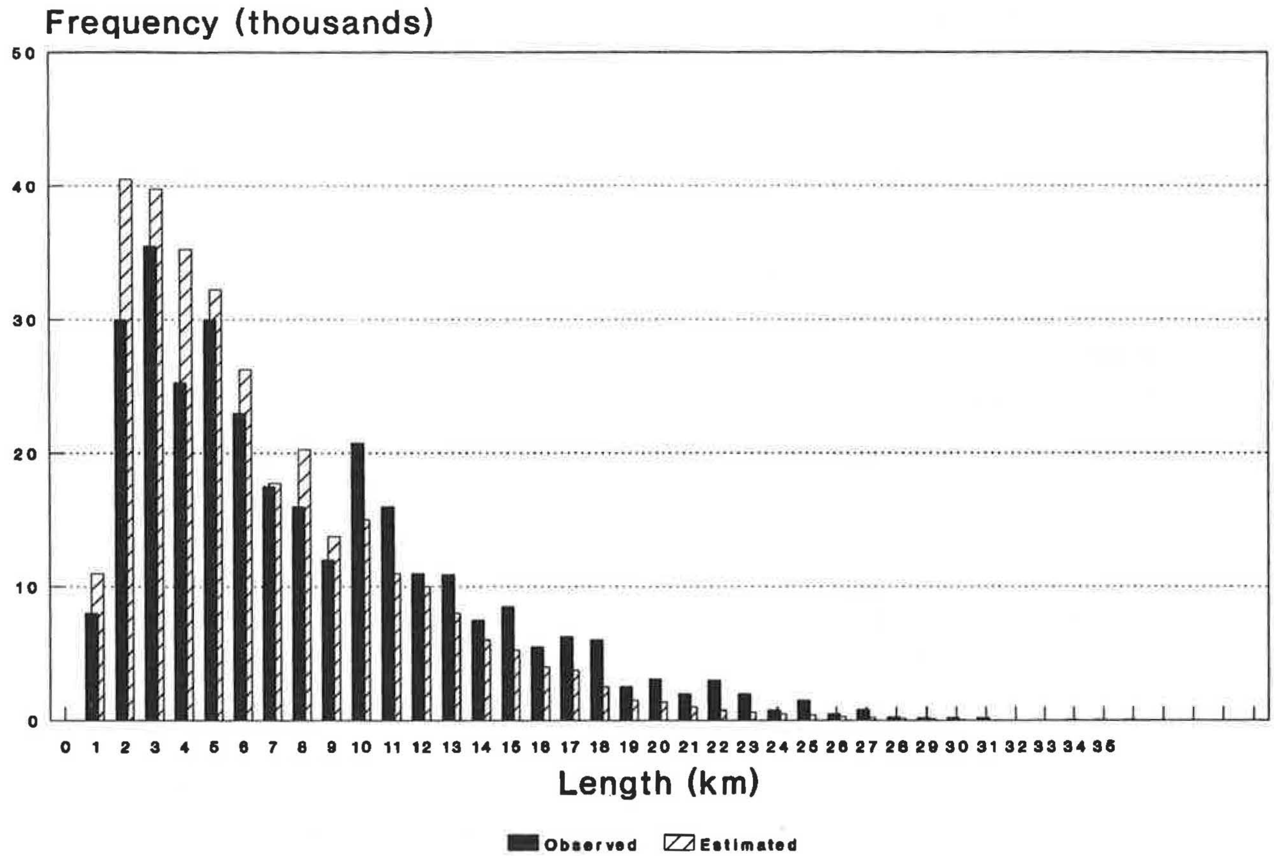

FIGURE 1 Observed and estimated trip length distributions for non-home-based trips in LITU 88.

TABLE 8 Logit Model for Household Car Ownership in LITU 88

Variable	Coefficient	Alternative
Income	0.2014	Car(s) in household
Household size	0.5881	Car(s) in household
Flat-dummy *	1.216	No car in household
City-dummy	1.418	No car in household
No car -dummy	2.302	No car in household

$\rho^2 = 0.468$

*Flat-dummy equals one if the household lives in an apartment house outside the city center and zero otherwise.

TABLE 9 Logit Model for the Division of the Population into HAP/EHAP* Categories in LITU 88

Variable	Coefficient	t	Alternative
Car in household (0/1)	3.093	27.9	HAP
Household income	0.06382	6.4	HAP
Number of workers in household	0.6438	10.5	EHAP
HAP-dummy	-2.658	-21.9	HAP

$\rho^2 = 0.347$

* HAP-person is a person that practically always has access to a car for personal trips. Others are EHAP-persons.

statistical indicators like ρ^2. One must also consider the performance of the models in forecasting.

During these comparisons, the alternative specific dummy variables of the original mode choice models were corrected by an iterative method, presented by Talvitie (*12*), to give a better replication of the present situation.

Some practical problems of the modeling work are also worth mentioning here. First, the travel times for buses were estimated with the EMME/2 system. The assignment procedure of the program tries to minimize the sum of the travel time of all passengers between each origin and destination pair (*8*). The procedure gives fairly stable total travel time, but its components (waiting, walking, and in-vehicle time) are very sensitive to the way the lines and network are coded. The assignment procedure also tends to give more transfers than are actually made during the trips.

The travel times for trains were calculated with a separate procedure where EMME/2 and some tailor-made programs were used. Here too the way the EMME/2 network was coded caused some problems in the estimation in station choice.

Second, the correct way of estimating the intrazonal distances and travel times, both in private and public transport, turned out to be problematic. The estimation was done in advance in network coding without direct connection to modeling, and this was probably one reason for the difficulties in replicating the correct trip length distributions. The intrazonal distances and travel times were originally coded in the 282-zone system. The aggregation of the zones to a 117-zone system has perhaps even strengthened the deficiencies of the values.

In spite of these difficulties, the forecasts of the model system described here turned out to be satisfactory in most cases. The forecasts so far were made with models with some theoretical deficiencies (for example, in the coefficient of the logsum variable), and many problems still exist. The estimation of new models is going on, and new forecasts will be made during spring 1992.

The final method of forecasting is still under discussion, too. There are three possible alternatives. The first is to use disaggregate models with zonal means as described here. The second is to make the forecasts using sample enumeration. This method has not been used in Finland earlier, and many practical problems have to be solved before full-scale applications. Sample enumeration will anyway be used to make further checks on model performance, especially in destination choice.

The third way to make the forecast is to use either the first or the second method to calculate growth factors that can be used to modify the present car and public transport trip matrixes. The basic idea of this method is to make better use of the trip matrixes that were explored with the big OD field surveys mentioned in this paper.

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Comparison of Suburban Commuting Characteristics

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Rapid growth in suburban population over the past two decades has inevitably turned once lightly traveled rural roads into heavy-traffic highways that require considerable investment for upgrading. However, such a need was not recognized in time to develop suburban-oriented traffic management strategies, and unprecedented levels of suburban congestion resulted. Mobility improvement in suburbs has thus become one of the most pressing transportation issues. In response to increasing public concern, reports and articles have been produced to explore various short- and long-term strategies. However, one vital aspect, a fundamental understanding of suburban commuting behavior, has not been adequately addressed in the transportation literature. An exploratory analysis is performed to characterize suburban commuting behavior on the basis of surveys conducted at three suburban activity centers. A comparison of the 14 travel and socioeconomic variables was performed first, followed by a discrete estimation of their relations with suburban workers' trip-stop frequency behavior. It has been found that suburban workers, even though from geographically different locations, reveal similar commuting patterns. The estimation results were further supported by a multivariate cluster analysis through which survey respondents from each location were classified into six groups of unique characteristics. Whereas each cluster of survey participants exhibits a similar pattern at these three locations, its shape varies substantially from the other five clusters. This confirms that in contending with suburban congestion different strategies should be developed to target different groups of suburban residents.

In the past several decades, concern over the growing severity of urban traffic congestion has led to migration of both population and business to suburbs. The nature and direction of suburban travel demand have changed significantly since the migration is often accompanied by major traffic generators such as shopping malls, office complexes, and recreation centers. In fact, because of a rapid increase in suburban population, the once dominant suburb-to-city-center commute has now been superseded by suburb-to-suburb travel.

The change in population and commuting patterns has taken place since the 1960s. Whereas center city and rural populations have remained relatively stable since then, most of the population increase has been in suburbs, where the national share of population grew from 23 percent in the 1950s to 40 percent in 1986. The rapid growth has inevitably turned once lightly traveled rural roads to heavy-traffic highways that require considerable investment for upgrading. However, such a need was not recognized in time to develop suburban-oriented traffic management strategies, from either the demand or the supply side. A failure to understand the changing role of suburbs, compounded by meager levels of transit services and a substantial curtailment in new road construction, has compelled suburban commuters to become more dependent on automobiles for accessing workplaces and has resulted in unprecedented levels of suburban congestion. Mobility improvement in suburbs has thus become one of the most pressing issues in transportation.

In response to increasing public concerns on this issue, reports, articles, and media accounts have been produced to explore various short- and long-term strategies. Most studies were conducted along the following two directions: (*a*) exploring the interrelations between land use development patterns and suburban traffic congestion (*1–10*) and (*b*) diagnosing suburban congestion problems and developing public policy options (*9,11–14*). Whereas these two dimensions are undoubtedly necessary in understanding the evolution of suburban land use patterns and travel demand, the development of effective strategies for traffic congestion requires better knowledge of suburban trip-making behavior. This vital aspect, however, has not received adequate attention in the transportation literature (*15*). One area where there has been very little research and where a considerable knowledge gap remains is in the differences between suburb-to-city-center and suburb-to-suburb trip-making behavior. That, in turn, precludes an effective use of valuable experiences obtained in contending with urban congestion (*16–18*) in improving suburban mobility.

In response to this research need, this paper focuses on the following two aspects: (*a*) understanding of suburban commuting behavior with an emphasis on the interrelations between commuting trip stop frequency and some background factors, and (*b*) classification of suburban commuters into several distinct groups with unique characteristics allowing for a better design of various demand management strategies.

SURVEY DESCRIPTION

The survey results presented in this paper were collected as part of NCHRP Project 3-38(2), "Travel Characteristics at Large-Scale Suburban Activity Centers." The primary purpose of this project was to develop a comprehensive data base on travel characteristics for various types of large-scale, multiuse suburban activity centers throughout the United States. Travel characteristics data were collected at six representative large-scale suburban activity centers through person and vehicle counts, workplace surveys, intercept surveys at hotel and retail sites, and daily trip diaries completed by residents of housing complexes within the activity centers. A detailed

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description of the sampling design and survey results can be found in *NCHRP Report 323* (*19*).

The survey results analyzed in this paper were taken from three workplace surveys completed at the Parkway Center, approximately 10 mi north of the Dallas central business district (CBD) in Texas; Tysons Corner, 12 mi west of downtown Washington, D.C., in Fairfax county, Virginia; and the Southdale Mall, located roughly 10 mi south of the Minneapolis CBD within the cities of Bloomington and Edina.

The Parkway Center consists of approximately 17 million ft^2 of office space, 7 million ft^2 of retail space (including three regional malls), 8 hotels with a total of more than 3,100 rooms, and 12,000 dwelling units. Workplace surveys were distributed to employers in 12 multitenant office buildings at the Parkway Center, containing approximately 4.3 million ft^2 and 6,900 employees. Employers were responsible for distributing the surveys to their employees and encouraging their returns. Of the 6,580 surveys distributed in these buildings, 1,781 were returned (27 percent), and 1,005 were completed and used in the analysis.

The Tysons Corner activity center has more than 13 million ft^2 of office space, a regional shopping mall, several hotels and high-rise residential buildings, and numerous shopping plazas. The workplace surveys were conducted in eight office buildings in which 8,522 survey forms were distributed. Of these surveys, 3,164 were returned (37.1 percent), and 2,194 were completed and used in the preliminary study. The Southdale activity center encompasses an area of roughly 4 million ft^2 of office space, several shopping plazas, numerous low-rise apartments, and condominium complexes. The workplace surveys were conducted in 21 office buildings and distributed to 13,231 employees. Whereas 3,951 people responded to the survey, only 3,313 answered all questions included in the survey form.

Workplace surveys consisted of three categories of questions: commuting characteristics, trip-making characteristics, and respondent background information. Questions pertaining to commuting characteristics are work location, commuting distance, travel times on morning and evening commutes, work starting time, and the commuting mode. The frequency of stops in work-to-home and home-to-work trips and the number of trips made per day constitute the category of trip-making characteristics. Also included are the purpose of each stop and the means of travel. The category of respondent background information comprises questions on age, sex, household size, occupation, and automobile ownership. Unfortunately, information on a critical variable, income level, was not asked for in the survey.

As is well recognized in travel behavior research, an individual's income level is a critical explanatory variable, and its omission may result in some difficulties in trip characteristics classification. It is also recognized that the relatively low response rate in all three suburban activity center (SAC) surveys may result in significant nonresponse bias. However, since the data set as well as the survey design are made available to the research community after the preliminary results have been published, the use of any sophisticated statistical methods for estimating the potential nonresponse bias is not feasible. Besides, the survey provides only a "snapshot" rather than a representative day of commuters' travel behavior, since questions on commute and trip-making characteristics were posed only for the current day. Nevertheless, the results of the survey contain useful information and provide a basis for understanding the complex suburban trip-stop frequency behavior.

PRELIMINARY ANALYSIS AND COMPARISON

The preliminary analysis starts with a comparison of key travel and background variables associated with survey respondents in the SACs. Table 1 presents the mean and standard deviation of 14 variables available from the three SAC surveys. The variables provide the profile of survey participants' background and their trip-stop frequency behavior. Since the three SACs were located in different states, a sequence of statistical tests, as shown in Figure 1, was performed to identify their key characteristic differences. For instance, Levene's test for variance homogeneity was conducted first for each variable. It was then followed by a simultaneous examination of sample means from the three SACs. A pairwise comparison with the least significance difference (LSD) method was further performed if the null hypothesis of equal means was rejected. The test results are summarized in Table 2, and their implications are briefly described as follows.

Despite the distinct geographical differences, the participants in the three SAC surveys reveal the following common characteristics: an average of 0.48 stops from work to home, an average automobile occupancy of 1.1 persons, and an average household size of 2.76 persons. These results seem consistent with the perception that suburban workers mostly have relatively small families, use the drive-alone mode on commutes, and often make some stops during their work-to-home trips. The apparently low automobile occupancy certainly contributes to the increasing suburban congestion and suggests the need to better understand suburban commuting behavior and to design effective demand management programs. We now discuss some variables that vary significantly across these three SACs.

- Average travel time to work and home: The statistical results in Table 2 indicate that suburban workers at Tysons Corner experienced the longest commuting time even with the same average travel distance as those working in the Parkway Center. Their average travel speed is about 26 mph, compared with 31 mph in Parkway and 33.8 mph in Southdale. This is mainly due to more severe traffic congestion in Northern Virginia than at the other two locations. Suburban workers in Southdale on average have the shortest travel time and commuting distance. Travel time reported by survey participants is actually the door-to-door time, including both the trip time and stop times for performing activities. The failure to separate these two components of travel time makes the analysis more difficult and is one of the major deficiencies of the survey design.
- Average stops from home to work: Suburban workers at the Parkway Center appear to make significantly more stops in their home-to-work trips than those at the other SACs. A further analysis of those trip purposes reveals that this is mostly due to the relatively high fraction (30 percent) of workers at Parkway Center who need to complete work as well as child-care-related activites on their morning commutes.

TABLE 1 Mean of Key Commuting Characteristics Obtained from Three SACs

Variables	Suburban Location		
	Parkway	Tysons	Southdale
1. Average stops from home to work	0.27 (0.60)	0.22 (0.56)	0.21 (0.54)
2. Average mid-day trips	0.64 (1.07)	0.84 (1.16)	0.62 (1.07)
3. Average stops from work to home	0.46 (0.77)	0.49 (0.81)	0.48 (0.82)
4. Travel time to work (minutes)	28.50 (14.73)	43.28 (18.95)	22.62 (12.39)
5. Travel time to home	31.50 (16.40)	37.03 (19.54)	25.66 (14.37)
6. Commuting distance	14.91 (12.04)	14.89 (10.79)	12.72 (10.03)
7. Total number of trips made per day	2.45 (0.57)	2.58 (0.60)	2.43 (0.58)
8. Auto occupancy	1.12 (0.51)	1.10 (0.47)	1.10 (0.47)
9. Average length of employment (years)	1.72 (1.43)	4.18 (4.43)	3.57 (4.11)
10. Household size	2.57 (1.21)	2.81 (1.26)	2.76 (1.24)
11. Average number of vehicles	1.97 (0.87)	2.21 (1.01)	2.12 (0.99)
12. Average number of children	0.55 (0.88)	0.49 (0.85)	0.54 (0.92)
13. Average number of full-time workers	1.34 (0.85)	1.51 (1.01)	1.49 (0.91)
14. Average number of part-time workers	0.15 (0.44)	0.25 (0.58)	0.33 (0.66)
Number of samples	1005	2194	3313

•Standard deviation for each cell is shown in the parentheses

• Average midday and total number of trips per day: The frequency of midday trips is defined as the number of trips made during the working hours on the day of survey. Some trips that take place in the same buildings, such as for meals in the mall, are not included in this category. The total number of trips refers to those made during both working and nonworking periods. As expected, suburban workers in Tysons Corner, a very large shopping area, made a significantly higher number of both midday trips and total trips per day than those in the other SACs. Most of those trips (more than 50 percent) were mainly for shopping rather than work-related activities. In contrast, the differences in these two variables between Parkway and Southdale workers are not statistically significant.

• Average number of available vehicles: The results of pairwise comparison indicate that there is no significant difference in the average number of vehicles per household between Tysons Corner and Southdale. Those in Parkway Center seem to own a relatively low number of vehicles, probably because of their relatively small family size and low number of full-time workers (see Table 1). Another reason may be their significantly shorter length of employment (1.72 years). Most respondents in Parkway are relatively young workers.

• Average length of employment: This varies particularly significantly among the three SACs. Whereas survey respondents at Tysons Corner indicate the longest employment (4.18 years), those from Parkway Center in Texas have a relatively short working experience (1.72 years). This is consistent with other observed characteristics that suburban workers at Parkway Center, compared with those from the other two SACs, on the average have the smallest household size and a relatively small number of full-time workers as well as vehicles available (see Table 1).

Given this preliminary comparison, we now explore the interrelations between principal survey variables. A classification of survey respondents with respect to the frequency of stops and travel time is summarized in Tables 3 and 4. Since all three SAC surveys reveal similar relations among key variables, only the results for Parkway Center are discussed.

Tables 3 and 4 classify commuting characteristics by the frequency of stops and travel time in work-to-home trips. Some variables exhibiting no systematic trends are not included in these tables. As expected, among the selected variables for travel measures, travel time to work appears to correlate posi-

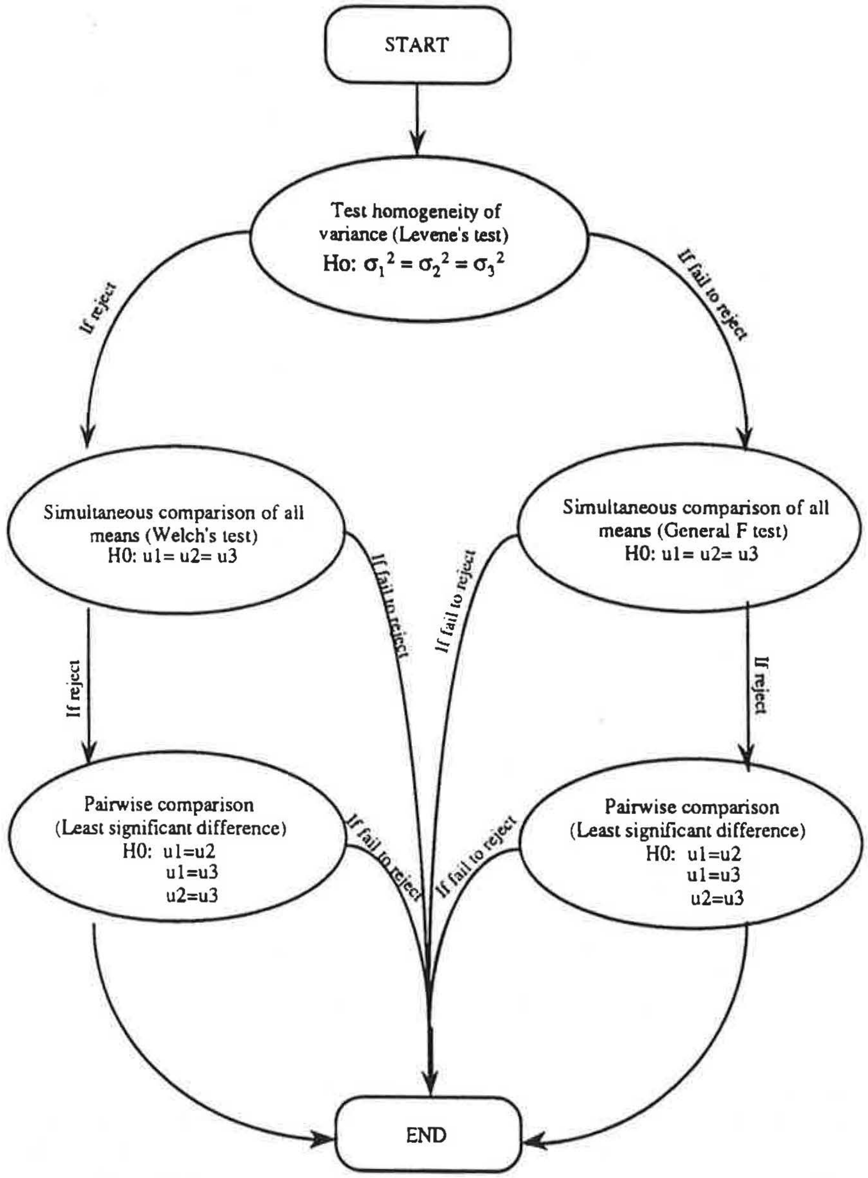

FIGURE 1 Procedures for comparing the survey results obtained from different activity centers.

tively with the frequency of stops both to home and to work, except in the last category (i.e., three or more stops), which contains only limited observations (14 in Table 1 and 20 in Table 2). This is consistent with the fact that given the same travel distance, a trip with more stops is expected to take a longer time. In contrast, the midday trip frequency (Table 4) seems to correlate negatively with the travel time both to home and to work, implying that people living near their workplaces tend to make more midday trips, going home either for meals or for work-related activities.

The frequency of stops both to work and to home appears to correlate with variables such as automobile occupancies, household size, and the number of working persons and children per family. With respect to automobile occupancy, a plausible explanation is that commuters having a high number of ridesharers are likely to stop more frequently to pick up or drop off other occupants. For similar reasons, respondents with large households and more children are often required to make more stops on their daily commutes.

The relations between the frequency of stops and other variables are not so distinct and thus cannot be observed directly at the aggregate level (i.e., from the computed average values). For instance, differences in the car ownership and in the number of working family members across all four categories do not exhibit any systematic trend with the frequency of stops. A more detailed investigation of such relations is presented in the next section.

Table 4 summarizes the commuting characteristics classified by travel time to work. Reported travel times of respondents are divided into five categories. To relate the travel time with the "average stops from home to work," it appears that respondents who experienced longer travel times (>40 min) generally made significantly more stops, possibly to pick up or drop off other passengers or children. In contrast, no sys-

TABLE 2 Equality Test for the Mean Value of Each Variable Obtained from Three SACs

Variables	Test Homogeneity of variance (H_0: $\sigma_1^2=\sigma_2^2=\sigma_3^2$)	Compare all mean H_0: $u_1=u_2=u_3$	Pairwise Comparison H_0: $u_1=u_2$ PW&TS	$u_1=u_3$ PW&SD	$u_2=u_3$ TS&SD
1. Average stops from home to work	R	R	R	NR	NR
2. Average mid-day trips	R	R	R	NR	R
3. Average stops from work to home	R	NR			
4. Travel time to work (minutes)	R	R	R	R	R
5. Travel time to home	R	R	R	R	R
6. Total number of trips made per day	R	R	R	NR	R
7. Auto occupancy	R	NR			
8. Average length of employment (years)	R	R	R	R	R
9. Household size	R	R	R	R	NR
10. Average number of vehicles	R	R	R	R	R
11. Average number of children	R	NR			
12. Average number of full-time workers	R	R	R	R	NR
13. Average number of part-time workers	R	R	R	R	R
14. Commuting distance	R	R	NR	R	R

* R: reject the null hypothesis at the 5% level of significance
** NR: fail to reject the null hypothesis at the 5% level of significance
*** PW: Parkway center; TS: Tysons Corner; SD: Southdale center.

tematic relation can be identified between the frequency of midday trips and the travel time to work. For instance, the group of respondents with very short commutes (<15 min) generated a significantly high frequency of midday trips. A further analysis of their trip purposes indicates that those with a high frequency of midday trips were mostly returning home for meals or family-related activities because of their relatively short travel distances. Those trips constitute about 40 percent of total observed midday trips at the Parkway Center.

Table 4 also indicates a positive correlation between automobile occupancy and travel time, implying that respondents with longer commuting distance (>26 mi) have experienced higher automobile occupancies. This is consistent with the perception that individuals with long commutes tend to form carpools more readily than those with short commutes. However, the average automobile occupancy is low in all categories, confirming that most trips were made by drive-alone commuters. Such a positive interrelation can also be observed in the following two pairs of variables: household size versus travel time and the average number of vehicles versus travel time. As indicated in Table 4, it appears that respondents from large households generally experienced longer commuting times than those from small households. This may be because individuals having fewer children are more likely to find affordable houses of adequate size within a shorter commuting range. The existence of a positive correlation between the travel time to work and the number of children seems to further support such an explanation.

Regarding the variable "average number of vehicles per household," it appears that respondents with longer commutes tend to own more vehicles. This may be due partly to the large household size for various activities and partly to poor transit services (e.g., 91 percent of trips use the drive-alone mode).

CLUSTER AND DISCRIMINANT ANALYSES

The preceding estimation provides the preliminary interrelations between suburban workers' commuting behavior and some of their background variables available from the surveys. To further understand their behavior patterns, it is natural to ask two questions: Can suburban commuters be classified into a number of distinct groups with a certain homogeneity in their behavior? Is it likely to identify each individual's travel pattern on the basis of associated factors such as socioeconomic background? Hence, in this section the method of cluster analysis is first applied to identify groups

TABLE 3 Classification of Commuting Characteristics by the Frequency of Stops to Work

Variables	Number of stops on the way to work				
	0	1	2	≥3	Total
1. Travel time to work(minutes)	27.53 (13.80)	32.84 (17.45)	34.37 (18.28)	**22.50** (13.28)	28.50 (14.73)
2. Average mid-day stops	0.61 (1.06)	0.68 (0.96)	0.81 (0.91)	1.43 (2.17)	0.64 (1.06)
3. Average stops from work to home	0.37 (0.68)	0.81 (0.85)	0.91 (1.27)	1.14 (1.40)	0.46 (0.77)
4. Total number of trips made per day	2.43 (0.57)	2.49 (0.54)	2.53 (0.50)	2.71 (0.83)	2.45 (0.57)
5. Auto occupancy	1.07 (0.39)	1.25 (0.69)	1.51 (1.10)	**1.36** (0.93)	1.12 (0.51)
6. Household size	2.48 (1.17)	2.84 (1.12)	3.28 (1.67)	**3.00** (1.24)	2.57 (1.21)
7. Average number of vehicles	1.98 (0.87)	1.91 (0.75)	2.02 (0.96)	2.43 (1.45)	1.97 (0.87)
8. Average number of children	0.47 (0.84)	0.81 (0.88)	1.09 (1.19)	**0.79** (1.05)	0.55 (0.88)
9. Average number of full-time workers	1.32 (0.87)	1.43 (0.75)	1.60 (0.88)	**1.21** (0.70)	1.34 (0.85)
10. Average number of part-time workers	0.14 (0.41)	0.16 (0.50)	0.26 (0.66)	0.36 (0.63)	0.15 (0.44)
Observations	807	141	43	14	1005

• **The standard deviation for each cell is shown in the parentheses**

TABLE 4 Classification of Commuting Characteristics by Travel Time to Work

Variables	Travel time to work (minutes)					
	(0-15)	(16-20)	(21-25)	(26-40)	(≥41)	Total
1. Average stops from home to work	0.27 (0.69)	0.20 (0.53)	0.19 (0.55)	0.27 (0.63)	0.41 (0.67)	0.27 (0.63)
2. Average mid-day stops	0.91 (1.31)	0.52 (0.99)	0.56 (0.85)	0.59 (1.07)	0.57 (0.88)	0.64 (1.07)
3. Average stops from work to home	0.48 (0.74)	0.45 (0.84)	0.37 (0.68)	0.41 (0.71)	0.60 (0.90)	0.46 (0.78)
4. Total number of trips made per day	2.58 (0.61)	2.34 (0.55)	2.43 (0.53)	2.41 (0.58)	2.42 (0.53)	2.45 (0.57)
5. Auto occupancy	1.057 (0.327)	1.078 (0.390)	1.081 (0.522)	1.167 (0.598)	1.198 (0.626)	1.121 (0.512)
6. Household size	2.16 (1.07)	2.47 (1.22)	2.67 (1.27)	2.66 (1.16)	2.98 (1.22)	2.57 (1.21)
7. Average number of vehicles	1.86 (0.98)	1.89 (0.78)	1.91 (0.69)	2.01 (0.83)	2.19 (0.94)	1.98 (0.87)
8. Average number of children	0.30 (0.67)	0.51 (0.86)	0.60 (1.01)	0.59 (0.84)	0.81 (1.03)	0.55 (0.88)
9. Average number of full-time workers	1.21 (0.86)	1.26 (0.84)	1.37 (0.87)	1.42 (0.85)	1.46 (0.83)	1.34 (0.85)
10. Average number of part-time workers	0.14 (0.42)	0.13 (0.43)	0.11 (0.33)	0.12 (0.40)	0.22 (0.58)	0.15 (0.44)
Observations	227	179	123	294	182	1005

• **The standard deviation for each cell is shown in the parentheses** of survey respondents with similar travel characteristics, and their similarities and differences among clusters and across different locations are compared. Travel characteristics variables used for clustering observations are travel time in work-to-home and home-to-work trips, total number of trips per day, frequency of stops in the work-to-home and home-to-work trips, and the number of midday trips. Each cluster is then characterized by six background descriptors, including the commuting distance, household size, the number of available vehicles, the number of children, the number of part-time workers, and the average length of employment.

As is noted in the statistical literature, a satisfactory method for determining the optimal number of clusters remains to be developed (*20,21*). Since the purpose of this study is to dissect observed travel behavior rather than to uncover "real clusters," it is generally sufficient to use R^2 for each variable and for all variables together to determine the appropriate number of clusters. With this logic in mind, observations from each survey were grouped into six distinct clusters on the basis of the centroid method available in the SAS package (*22*). The selection of six clusters is based on an extensive experimental analysis, which consists of three principal steps: (*a*) classification of survey respondents into a preselected number of clusters, ranging from two to nine; (*b*) development of a linear discriminant function for each cluster with its background descriptors; and (*c*) computation of the posterior probability for each individual who is then assigned to the cluster of highest probability. The degree of success achieved in classifying survey respondents to their original clusters was then measured. An investigation has indicated that the selection of six clusters has yielded the best results, which can successfully predict the travel pattern (i.e., the assigned cluster) of the 72 percent of survey participants on the basis of only the six background descriptors.

Table 5 summarizes the cluster means and standard deviations of the six travel-related variables, indicating the variation of individual travel behavior in different clusters. Five of the six clusters in all three SACs exhibit two distinct patterns: the travel time to home is consistently longer than the travel time to work, and the frequency of stops in work-to-home trips is higher than that in home-to-work trips. These two systematic patterns are logically consistent, because the time for each stop constitutes a fraction of the total travel time. Thus, given the same travel distance, it is reasonable to expect a longer travel time if more activities are conducted during the trip. These two consistent patterns seem to represent the common features of suburban commuting behavior (except for the 38 individuals in Cluster 2). Some unique character-

TABLE 5 Cluster Means of Travel-Related Variables

Cluster	Location	TRW	TRH	TNP	NSW	NSH	NMT	Sample
	Parkway	34.20	35.27	2.53	2.47	2.86	0.73	15
1	Tysons	60.36	64.85	2.73	1.73	2.39	1.24	33
	Southdale	60.07	71.73	2.60	2.40	2.58	1.27	15
	Parkway	27.26	26.29	2.58	2.29	0.18	0.95	38
2	Tysons	33.78	32.24	2.53	2.53	0.55	0.90	49
	Southdale	27.76	33.36	2.42	0.62	1.03	0.55	507
	Parkway	25.55	28.57	2.36	0.11	0.23	0.40	717
3	Tysons	25.19	27.46	2.48	0.10	0.23	0.57	1265
	Southdale	15.01	16.61	2.34	0.10	0.18	0.40	1576
	Parkway	55.14	62.07	2.37	0.36	0.59	0.45	106
4	Tysons	57.76	61.16	2.49	0.18	0.31	0.67	522
	Southdale	33.30	38.94	2.34	0.12	0.01	0.40	797
	Parkway	25.62	29.62	2.39	0.29	2.36	0.50	66
5	Tysons	32.00	36.54	2.67	0.29	2.27	0.94	198
	Southdale	19.72	25.00	2.44	0.27	2.07	0.63	263
	Parkway	19.71	21.30	3.54	0.21	0.52	3.67	63
6	Tysons	25.14	28.61	3.76	0.16	0.46	4.06	127
	Southdale	19.26	20.85	3.76	0.21	0.35	4.13	155
	Parkway	0.40	0.42	0.25	0.62	0.55	0.61	
R^2	Tysons	0.49	0.51	0.26	0.19	0.53	0.76	
	Southdale	0.54	0.54	0.25	0.52	0.49	0.59	

TRW: Travel time to work, including both stop and commuting times (minutes).
TRH: Travel time to home, including both stop and commuting times (minutes).
TNP: Total number of trips made per day.
NSW: Total number of stops on way to work.
NSH: Total number of stops on way to home.
NMT: Total number of mid-day trips.

istics associated with each cluster are briefly discussed in the following paragraphs.

In all three SACs, Cluster 1 contains the smallest fraction of respondents (15 people in both the Parkway and Southdale SACs and 33 in Tysons Corner). In comparison with the other five clusters, suburban workers in this cluster have the following unique characteristics: (*a*) the highest frequency of stops in their work-to-home trips, (*b*) either the highest or the second highest number of stops on their home-to-work commutes, (*c*) the largest household size and the largest number of children, (*d*) the lowest number of vehicles per household, and (*e*) the longest or the second-longest commuting distance. The fact of having a large family size and a relatively long commuting distance, along with the lack of adequate vehicles, seems to explain their need to stop more frequently than others on daily commutes. This is consistent with the fact that 90 percent of commuters in Cluster 1 use carpools as the main commuting mode.

Cluster 1 workers not only exist in all three SACs but also have similar travel and socioeconomic patterns. Although they may be a relatively small fraction of suburban residents, and most of them have low income and large household size, they need more help and are the potential users of effective suburban public transportation systems.

In all three SACs, suburban workers in Cluster 2 feature a high frequency of stops in work-to-home trips. Among the six clusters, they have on the average the highest or second-highest number of stops on the evening commute and the largest or second-largest number of children. In addition, as indicated in Table 6, they tend to have a relatively large household size and part-time workers, and they make frequent trips in the middle of a working day.

Both Tysons Corner and Parkway survey results indicate that Cluster 2 workers' frequency of stops on their way to work is much higher than that in their work-to-home trips (2.29 versus 0.18 in Parkway). This seems contrary to the assertion that commuters tend to stop less frequently in their trips to work than to home because of the concern of being late to work as revealed in the commuting patterns of respondents in the other five clusters. To understand the underlying reasons, the trip purpose of home-to-work stops made by Cluster 2 respondents was further investigated. It was found that the work- and child-care-related stops constitute 55 percent of the 83 stops made by them (in Parkway) during the morning commute. The two main reasons for those intermediate stops do not exist for this cluster of people in their evening returning trips and account for less than 10 percent of the total stops incurred. A similar pattern exists for those working in Tysons Corner.

In all three SACs, Cluster 3 consistently consists of the largest fraction of respondents (e.g., 717 out of 1,005 people in Parkway), representing the typical suburban workers. As indicated in Table 5, this cluster is distinguished from others with its (*a*) lowest mean frequency of stops in home-to-work

TABLE 6 Cluster Means of Background Variables

Cluster	Location	FR	CD	HS	NVH	NCH	NPW	EL
1	Parkway	0.73	16.33	3.27	1.80	1.13	0.33	1.92
	Tysons	0.73	25.39	3.12	1.79	1.06	0.15	3.66
	Southdale	0.80	31.27	3.53	1.97	1.13	0.60	1.79
2	Parkway	0.66	11.18	3.13	2.08	0.95	0.21	1.70
	Tysons	0.61	12.82	3.10	2.22	0.65	0.30	3.65
	Southdale	0.75	15.75	2.81	1.99	0.70	0.27	3.31
3	Parkway	0.57	13.05	2.48	1.93	0.48	0.13	1.68
	Tysons	0.41	11.11	2.73	2.20	0.41	0.26	4.44
	Southdale	0.68	7.97	2.68	2.14	0.42	0.38	3.93
4	Parkway	0.64	32.72	3.03	2.33	0.84	0.21	1.81
	Tysons	0.51	25.32	2.97	2.22	0.65	0.26	3.65
	Southdale	0.62	21.14	2.93	2.21	0.66	0.28	3.01
5	Parkway	0.76	12.30	2.52	1.88	0.59	0.20	1.96
	Tysons	0.60	13.58	2.76	2.20	0.47	0.19	3.80
	Southdale	0.83	9.89	2.57	1.98	0.56	0.26	3.90
6	Parkway	0.48	10.70	2.40	2.00	0.46	0.14	1.79
	Tysons	0.39	10.14	2.75	2.33	0.45	0.19	4.65
	Southdale	0.45	10.78	2.81	2.02	0.59	0.36	3.20

FR: Female commuters/total number of commuters
CD: Commuting distance (miles)
HS: Household size
NVH: Number of vehicles per household
NCH: Number of children per household
NPH: Number of part-time workers per household
EL: Length of employment (years)

trips (e.g., 0.11 stops in Parkway), far below the mean value of all respondents; and (*b*) the smallest or second-smallest number of children. In addition, those individuals, as indicated in Table 6, are mostly from small households and have relatively short commutes (e.g., <15 mi). This is consistent with previous findings that commuters from small households are likely to live relatively near their workplaces.

Among the six clusters, survey respondents in Cluster 4 have the following consistent features in all SACs: the longest or second-longest mean travel time and commuting distance and the lowest or second-lowest midday trips. In addition, those individuals generally have a large household size (e.g., 3.03 persons in Parkway), a large number of part-time workers, children, and available vehicles. This conforms with previous findings that respondents having a large family tend to move toward distant suburbs to own an adequately large house within an affordable price range. To accommodate the long commuting distance and multiple workers per family, those individuals often own more than one vehicle, as indicated in the survey results.

In all three SACs, Cluster 5 is set apart from the other groups because of the uniquely high ratio (about 8:1) of work-

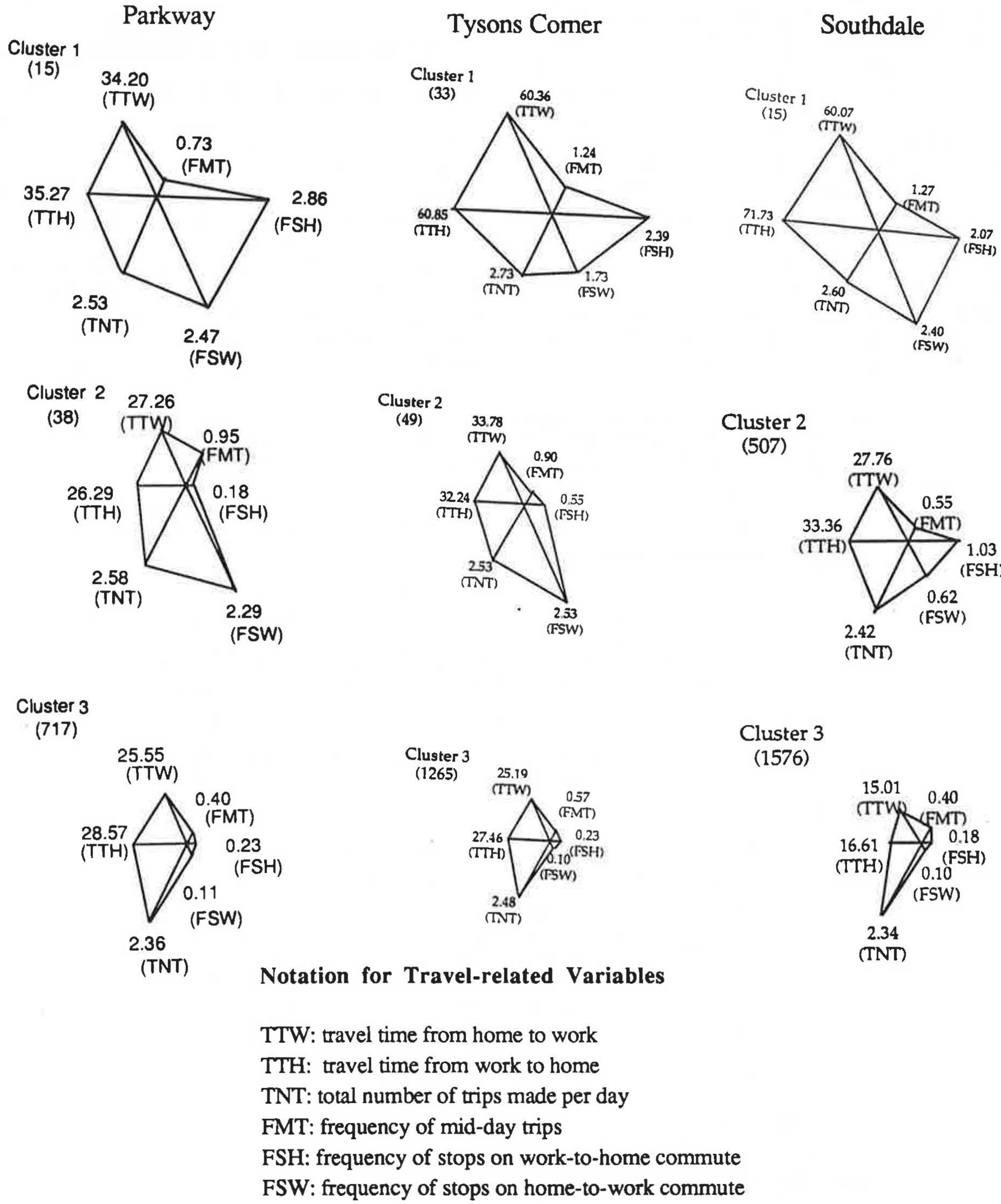

FIGURE 2 Travel-related variables for each cluster. (*continued on next page*)

to-home stops versus home-to-work stops and because it has the largest or second-largest proportion of females. A further analysis of trip purposes indicates that the high frequency of stops in returning trips are mainly due to their needs for shopping and recreation-related activities, which constitute around 68 percent of the total stops. Those individuals are mostly female, having relatively long employment experience but a relatively low number of children and available vehicles.

Cluster 6 stands out from the others with its highest fraction of males and largest number of midday trips in all three SACs. As indicated in Table 6, most respondents in this cluster have a relatively small family and can thus afford to live in a small house close to their workplaces. The resulting short commuting distance appears to account for their high-frequency of midday trips, mostly (about 72 percent) for coming home for meals or family-related activities. This is also consistent with the previous finding that the frequency of midday trips is correlated negatively with commuting distance or travel time.

To further compare the overall travel pattern between clusters in different SACs, each cluster is represented with one star plot in Figure 2. In comparing the shape of star plots, it is noticeable that in all three SACs the travel pattern varies significantly among clusters, indicating the existence of unique

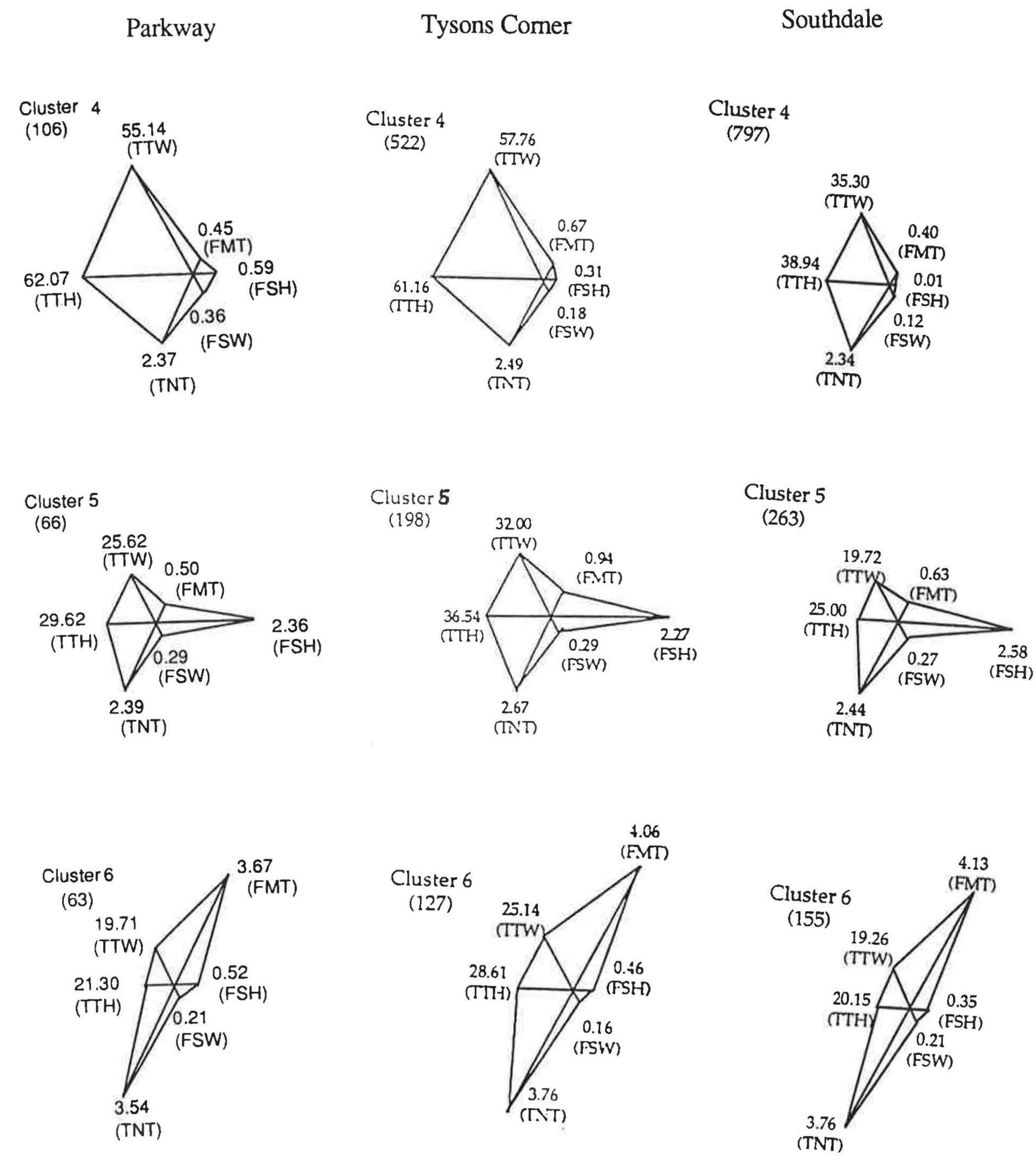

FIGURE 2 *(continued)*

travel characteristics for each group of individuals. In contrast, except for a slight difference in the shape for Cluster 2, the other five clusters, after being standardized, exhibit consistent patterns across the three locations in their travel-related measures. This seems to suggest that the possible overlap among clusters is negligible, and the application of such an approach has indeed yielded a reasonable classification of suburban commuting patterns.

In brief, even though the three suburban surveys were conducted from different regions, survey respondents can be classified into six consistent clusters, each having a similar pattern across the three SACs. Such distinct suburban commuting patterns should encourage transportation planners to develop diversified demand management strategies to serve each target group of suburban workers.

CONCLUSIONS

This paper has investigated suburban travel behavior with an emphasis on the interrelations between survey respondents' socioeconomic background and their manifested behavior patterns, especially concerning their frequency of stops to work and to home. In the absence of individual income information it has been found that variables such as work starting time, sex, commuting automobile occupancy, and available vehicles per family are significantly correlated with suburban workers' choices of stop frequency on their daily commutes. Single- and multiple-stop workers show different levels of sensitivity to any changes in these critical factors.

It has also been observed that suburban workers of relatively large households and limited employment experience tend to reside in relatively distant suburbs to afford houses of adequate size. To cope with the long commuting distance and the meager level of transit service, most suburban workers, as indicated in the survey results, were compelled to choose the drive-alone mode.

To further compare suburban commuting behavior, a multivariate cluster approach was used to classify survey respondents on the basis of selected travel characteristic variables. The results indicate that regardless of the geographical differences in the three SACs, suburban workers in each cluster exhibit similar travel as well as background patterns. In contrast, substantial differences among clusters exist, suggesting that different strategies or plans should be developed for different groups of suburban residents to effectively relieve suburban congestion.

Because of limitations of the original survey design, this research provides only preliminary understanding of complex suburban commuting behavior. To effectively contend with suburban congestion, much remains to be learned about the interrelations between suburban workers' background, behavior, and responses to different transportation management strategies. For instance, an ongoing research task is to understand the distribution of trip purposes on commutes and in the midday. The likelihood of minimizing those trip stops or changing their patterns can then be investigated.

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Estimating Availability Effects in Travel Choice Modeling: A Stated Choice Approach

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Existing stated preference models in the transportation literature focus principally on measuring preferences for travel alternatives. Choices are predicted by making ad hoc and possibly incorrect assumptions regarding the relationship between preference structures and choice behavior. In contrast, stated choice models are derived from choice data observed under hypothetical conditions. These models provide a powerful approach to testing simultaneously the assumed choice model and specification of the implied utility function. Nevertheless, conventional stated choice models are based on the rigorous assumption that the nonavailability of a particular travel alternative does not affect the utility and relative choice probability of any other travel alternative included in a choice set. How designs that permit the estimation of such availability effects can be constructed is indicated. A case study on mode choice behavior in the Eindhoven region, the Netherlands, suggests that choice models incorporating such availability effects can improve the predictive success of mode choice models. The results suggest that people's preferences for choosing the car to commute are only slightly influenced by the availability of modes of public transportation.

The continued demand for environmental quality coupled with growing car availability ratios has led many governments to design transport policies that aim at reducing car use by stimulating public transportation. This development increases the importance of obtaining defensible measures of the impact of such transport policies. To allocate resources efficiently and effectively, transport planners require information on the costs and the likely choices or changes in choices that might result from the implementation of various planning alternatives.

Over the years, various modeling approaches have been suggested in the literature and applied to real-world transport planning problems to provide the required information. One such approach that has gained increasing interest in the transportation literature over the last decade is the stated preference or decompositional preference approach (*1–8*). In contrast to conventional models that are based on actual travel choices, stated preference models are derived from experimental design data (*3,9,10*). Individuals are typically presented a series of hypothetical travel alternatives, constructed according to the principles of the design of statistical experiments, and asked to express their strength of preference for each alternative. The overall preference measurements are then decomposed into part-worth utilities associated with the attribute levels used to describe the hypothetical travel alternatives. Choice behavior is predicted by assuming some functional relationship between preferences and overt behavior (*11*).

Stated preference models have been applied successfully in a variety of transport contexts such as long-distance travel choice (*12*), competition between coach and rail (*13,14*), preferences for bus services (*14,15*), preferences for rail services (*16,17*), the effects of area licensing proposals (*18*), route choice (*19,20*), valuation of travel time (*21,22*), destination choice (*23–28*), and the effect of transport facilities on residential choice behavior (*29*).

Nevertheless, stated preference models have not escaped criticisms. A fundamental objection to stated preference models has been that it is not readily evident that individuals will act in hypothetical situations in a way that resembles how they would act in the real world. A related concern is that individuals may not be able to carry out the experimental task in a way corresponding to their actual decision making. These concerns have stimulated methodological research indicating that the assumption that conventional models based on actual behavior are inherently superior no longer goes unchallenged. Still, preference models rely typically on ad hoc assumptions to relate preferences to choice probabilities.

Recently Louviere and Woodworth (*30*) have therefore suggested that choices rather than preferences be measured in controlled experiments. One then observes choices directly and does not have to make ad hoc assumptions regarding the relationship between preferences and overt choice behavior. This is not to say that choices in laboratory settings may not differ from choices in the real world. Thus, even though the choice experiments have some potential methodological advantages over preference experiments, one still has to demonstrate that expressed choices are systematically related to observed choices. In these stated choice experiments individuals are not asked to rate or rank a series of hypothetical travel alternatives, but rather to choose among them. To estimate the choice model, the travel alternatives are placed into choice sets, usually using 2^N (N is the number of alternatives) or fractional factorial designs. Louviere and Woodworth (*30*) and Louviere and Hensher (*31*) have formalized the necessary and sufficient conditions that experimental designs must meet to satisfy the statistical requirements of the multinomial logit (MNL) model that is typically used in this

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modeling approach. Louviere and Hensher (*31*) present two examples of this approach to forecast mode choice behavior.

A problem common to all these decompositional preference and choice models is the rigorous assumption that preferences and choices are independent of context. That is, these models typically assume that individuals form preferences for alternatives or choose among alternatives independently of the composition of the choice set. In the MNL model, this problem stems from the independence from irrelevant alternatives (IIA) property, which states that the utility of a particular choice alternative is independent of the existence and the attribute values of any other choice alternative included in a choice set. Consequently, pairwise choice probabilities are independent of choice set composition. This assumption of context independence is rather rigorous because one might hypothesize that the availability or nonavailability of some transport mode will affect individuals' preferences/utilities or choices for the remaining available modes.

Louviere (*32*) indicates how to develop experimental designs that allow one to test for violations of the IIA property underlying MNL models and estimate generalized choice models, but applications of this approach in transportation are restricted to problems of destination choice (*33,34*) and have concentrated on substitution effects. One would like to be able to estimate the impact of varying choice set compositions on (pairwise) choice probabilities.

The purpose of this paper, therefore, is to extend conventional stated preference and choice models to allow the estimation of availability effects and illustrate this approach in the context of transportation mode choice.

STUDY DESIGN

In an attempt to reduce car use, the Dutch Ministry of Transport has created new planning authorities (transport regions) whose task is to coordinate transport plans. These planning bodies have to develop various kinds of plans to stimulate public transport and carpooling, thereby reducing the use of the car for all kinds of daily activities. These planning authorities need information on the likely impacts of such policy decisions on travel choice behavior. This study is an attempt to develop a sophisticated stated choice model that may serve this purpose.

To estimate a stated choice model, one first has to decide on the travel options and their attributes that are varied in the experiment. Five mode choice alternatives were identified: car, train, carpooling, bus, and bicycle. Bicycle was used as a base alternative in the experimental design, implying that all results obtained are relative to the estimated utilities and choice probabilities for using the bicycle. Using a literature search and interviews with planners, the attributes presented in Table 1 were selected because these attributes affect individual mode choice behavior most or are of planning interest. Commuting journeys were selected as the context of interest because these account for a high proportion of actual travel distances.

The attributes used in the experiment were alternative-specific. Four attributes were selected to describe the car alternative: in-vehicle time, costs, in-vehicle delay, and walking distance. Each of these attributes was varied in terms of three attribute levels. The train alternative was described by seven attributes: in-vehicle time, fare, in-vehicle delay, walking distance, delay in departure time, comfort, and interchange. Six of these attributes were varied in terms of three levels; the remaining attribute (interchange) had two levels. Carpooling was represented by six three-level attributes: in-vehicle time, costs, in-vehicle delay, walking distance, delay in departure time, and driver. The bus alternative was described in terms of seven attributes: in-vehicle time, fare, in-vehicle delay, walking distance, delay in departure time, comfort, and interchange. In addition to these alternative-specific attributes, distance from home to place of work was selected as a generic background attribute. The levels of all numerical attributes were adjusted to distance traveled (see Table 1). Some of the attribute levels were made specific to distance to make the profiles more realistic. For the car and carpooling, walking distance included the walk from the parking lot to the job location; for the two other means of transportation, walking distance included the distance from home to the bus stop or railway station and from the railway station or bus stop to the job location.

The Eindhoven region in the Netherlands was chosen as the study area, primarily because the planning authorities indicated some interest in this research project and were willing to provide the funds required to distribute the questionnaires. In general, the region has a good supply of various kinds of public transport, but of course not every municipality has a train station, and the quality of bus service differs substantially among the municipalities. Also, carpooling schemes are not equally well developed in all parts of the region. Therefore, it seems that the Eindhoven region is perfect for examining availability effects.

The survey was undertaken in January 1991. Of the 2,150 questionnaires sent by mail to randomly selected households in the region who were asked to participate in this study provided they had a job, 347 usable questionnaires were returned after one follow-up attempt, a response rate of 16.1 percent. This may seem a low figure, but it should be remembered that unemployment rates and the proportion of retired people in the Netherlands are rather high. Although exact figures are not available, we believe that the response rate for the population of interest is roughly 30 to 40 percent. Unfortunately, the representatives of the sample could not be tested because of lack of relevant population statistics. The sample respondents account for 7,293 monthly commuter journeys, an average of 19.3 journeys per month per person. The average travel distance per trip is 16.22 km. Of these trips, 53.1 percent are made by car, 34.8 percent by bicycle, 4.0 percent by carpooling, 2.8 percent by bus, and 3.2 percent by train.

In addition to completing the stated choice task, the respondents were asked to provide information relating to their actual travel choices, their evaluation of features of the regional transport system, and the socioeconomic characteristics of their households. The results of analyses incorporating these variables are not reported in this paper. We focus on an illustration of the model specification and the design strategy.

DESIGN STRATEGY

When the IIA property is not satisfied, one approach is to introduce terms into the systematic component of the utility

TABLE 1 Names and Levels of Attributes

Attribute	distance	level 1	level 2	level 3
CAR:				
In-vehicle travel time in minutes	8 km	7.5 min.	10.0 min.	12.5 min.
	16 km	15.0 min.	20.0 min.	25.0 min.
	24 km	20.0 min.	30.0 min.	40.0 min.
In-vehicle delay in minutes	8 km	0.0 min.	2.0 min.	4.0 min.
	16 km	0.0 min.	4.0 min.	8.0 min.
	24 km	0.0 min.	6.0 min.	12.0 min.
Walking distance in minutes	8 km	1.0 min.	3.0 min.	5.0 min.
	16 km	1.0 min.	3.0 min.	5.0 min.
	24 km	1.0 min.	3.0 min.	5.0 min.
Costs in guilders	8 km	fl. 2.00	fl. 3.00	fl. 4.00
	16 km	fl. 3.00	fl. 5.10	fl. 7.20
	24 km	fl. 4.40	fl. 7.00	fl. 9.60
BUS:				
In-vehicle travel time in minutes	8 km	10.0 min.	15.0 min.	20.0 min.
	16 km	20.0 min.	30.0 min.	40.0 min.
	24 km	30.0 min.	45.0 min.	60.0 min.
Delay in departure time in minutes	8 km	0.0 min.	3.0 min.	6.0 min.
	16 km	0.0 min.	3.0 min.	6.0 min.
	24 km	0.0 min.	3.0 min.	6.0 min.
In-vehicle delay in minutes	8 km	0.0 min.	2.0 min.	4.0 min.
	16 km	0.0 min.	4.0 min.	8.0 min.
	24 km	0.0 min.	6.0 min.	12.0 min.

(continued on next page)

TABLE 1 *(continued)*

Attribute	distance	level 1	level 2	level 3
Walking distance	8 km	2.0 min.	5.0 min.	8.0 min.
in minutes	16 km	2.0 min.	5.0 min.	8.0 min.
	24 km	2.0 min.	5.0 min.	8.0 min.
Fare	8 km	fl. 1.00	fl. 1.50	fl. 2.00
in guilders	16 km	fl. 1.50	fl. 2.50	fl. 3.50
	24 km	fl. 2.00	fl. 3.00	fl. 4.00
Comfort	8 km	2.0	5.0	8.0
on a 0-10 scale	16 km	2.0	5.0	8.0
	24 km	2.0	5.0	8.0
Interchange	8 km	none	1	
	16 km	none	1	
	24 km	none	1	
CARPOOLING:				
In-vehicle travel	8 km	7.5 min.	10.0 min.	12.5 min.
time in minutes	16 km	15.0 min.	20.0 min.	25.0 min.
	24 km	20.0 min.	30.0 min.	40.0 min.
Delay in depar-	8 km	2.0 min.	5.0 min.	8.0 min.
ture time in	16 km	2.0 min.	5.0 min.	8.0 min.
minutes	24 km	2.0 min.	5.0 min.	8.0 min.
In-vehicle delay	8 km	0.0 min.	2.0 min.	4.0 min.
in minutes	16 km	0.0 min.	4.0 min.	8.0 min.
	24 km	0.0 min.	6.0 min.	12.0 min.
Walking distance	8 km	1.0 min.	3.0 min.	5.0 min.
in minutes	16 km	1.0 min.	3.0 min.	5.0 min.
	24 km	1.0 min.	3.0 min.	5.0 min.

(continued on next page)

TABLE 1 *(continued)*

Attribute	distance	level 1	level 2	level 3
Costs	8 km	fl. 1.00	fl. 1.50	fl. 2.00
in guilders	16 km	fl. 1.50	fl. 2.50	fl. 3.50
	24 km	fl. 2.20	fl. 3.50	fl. 4.80
Who drives	8 km	self-drive;	passenger;	flexible
	16 km	self-drive;	passenger;	flexible
	24 km	self-drive;	passenger;	flexible
TRAIN:				
In-vehicle travel	8 km	7.5 min.	10.0 min.	12.5 min.
time in minutes	16 km	10.0 min.	15.0 min.	20.0 min.
	24 km	15.0 min.	20.0 min.	25.0 min.
Delay in depar-	8 km	0.0 min.	3.0 min.	6.0 min.
ture time in	16 km	0.0 min.	3.0 min.	6.0 min.
minutes	24 km	0.0 min.	3.0 min.	6.0 min.
In-vehicle delay	8 km	0.0 min.	1.0 min.	2.0 min.
in minutes	16 km	0.0 min.	2.0 min.	4.0 min.
	24 km	0.0 min.	3.0 min.	6.0 min.
Walking distance	8 km	2.0 min.	5.0 min.	8.0 min.
in minutes	16 km	2.0 min.	5.0 min.	8.0 min.
	24 km	2.0 min.	5.0 min.	8.0 min.
Fare	8 km	fl. 1.60	fl. 2.00	fl. 2.40
in guilders	16 km	fl. 2.00	fl. 3.00	fl. 4.00
	24 km	fl. 2.40	fl. 4.00	fl. 5.60

(continued on next page)

TABLE 1 *(continued)*

Attribute	distance	level 1	level 2	level 3
Comfort	8 km	2.0	5.0	8.0
on a 0-10 scale	16 km	2.0	5.0	8.0
	24 km	2.0	5.0	8.0
Interchange	8 km	none	1	
	16 km	none	1	
	24 km	none	1	

functions to represent the violations. If these terms are the levels of the attributes of the competing transportation modes, they are called attribute cross effects. If the terms represent the presence or absence of competing modes, they are called availability cross effects.

The general problem of optimal design for such discrete choice experiments is unsolved. Anderson and Wiley (*35*) have constructed locally optimal designs for the case in which alternatives are characterized by name only, and hence only availability cross effects need to be estimated. Lazari (*36*) and Lazari and Anderson (*37*) have considered the discrete choice set problem, in which both availability and attribute cross effects are present and there is only one attribute for each alternative. They provide an extensive catalog of designs for practical numbers of choice sets. General solutions are not available when the number of attributes for each alternative is large, except along the lines of this study.

For this study, the underlying design consisted of orthogonal fractional factorial designs arranged in a balanced incomplete block structure plus another orthogonal design with all modes present. The resulting design allows for estimation of mode-specific models including all mode-specific main effects, attribute cross effects, and availability cross effects. For the purpose of this paper only the mode-specific main effects and the availability cross effects have been estimated.

The following strategy was used to develop the experimental design that allows the estimation of availability effects. Remember that we have four travel modes (car, train, carpooling, and bus) with respectively four, seven, six, and seven attributes, and the bicycle as a base alternative. In addition, we have distance as a background variable. All of the attributes were assigned three levels, except the number of interchanges for bus and train, which only have two levels. First, a 54 treatment combination orthogonal fraction of the resulting $3^{23} * 2^2$ full factorial design was used to create choice sets of fixed size. These choice sets varied in terms of the descriptions of the four travel alternatives. Next, for each of the six pairs of travel alternatives $[6 = (4 \times 3)/2]$, an orthogonal fraction consisting of 36 treatment combinations was selected from the corresponding full factorial designs to allow the estimation of availability effects. The full factorial design representing all possible profiles for the car is a 3^4 design; the bus and train profiles both involve a $2 * 3^6$ design; and the carpooling profiles imply a 3^6 design. Thus, for example, the full factorial design for the car versus bus option involves a $(3^4 + 2 * 3^6) = 2 * 3^{10}$ design. Likewise, the bus versus train option involves a $(2 * 3^6 + 2 * 3^6) = 2^2 * 3^{12}$ design. For all pairs of travel modes, a 36 treatment combination orthogonal fraction describing the two travel modes was selected from the corresponding full factorial design. The two designs were combined to create an overall design. Thus, in total, $54 + (6 * 36) = 270$ choice sets were created. Although this design strategy does not generate a perfectly orthogonal design as a result of the merging of the separate designs, the overall correlations are generally very low. The highest correlation that we observed was only -0.0022.

Each respondent was presented three randomly selected choice sets from the 54 treatment combinations design and two randomly selected choice sets from each of the paired comparison, 36 treatment designs. Thus, in total, each respondent was presented $3 + (6 * 2) = 15$ choice sets. Respondents were told to assume that only the travel modes described in a choice set were available for commuting. They were also informed that the travel modes described in the various choice sets differ in terms of the attribute levels as indicated previously. The descriptions of the available travel modes were displayed on a single sheet. Respondents were asked to allocate 20 trips among the travel alternatives included in each choice set given that only the ones listed in a particular choice set are available. This task was repeated twice: once for the summer situation and once for the winter situation. Care was taken that respondents fully understood the experimental task and that they were familiar with the attributes and their levels used in the experiment. Before presenting the experimental task, respondents were asked to evaluate separately the attribute levels. Moreover, the task was explained in detail using an example, and respondents were asked to make sure they understood their task before completing the questionnaire.

The questionnaire was extensively pretested; the version that was finally used was the third version that was pretested.

ANALYSIS

Attribute Effects

The allocation data were aggregated across respondents to relative frequencies. Iterative reweighted least squares analysis was used to estimate the choice model. The following model was estimated:

$$p_{j|S} = \exp(V_{j|S}) / \sum_{j' \in S} \exp(V_{j'|S}) \tag{1}$$

$$V_{j|S} = \alpha_j + \sum_{j' \in S \setminus \{j\}} \gamma_{j'j} + \sum_{k=1} \beta_{jk} X_{jk} \tag{2}$$

where

$p_{j|S}$ = probability that travel alternative j in choice set S will be chosen,
$V_{j|S}$ = deterministic part of the utility of j in choice set S,
α_j = alternative-specific constant for alternative j,
$\gamma_{j'j}$ = availability effect of alternative j' on alternative j,
β_{jk} = parameter for the kth attribute of the jth travel alternative, and
X_{jk} = value of attribute k of travel alternative j.

Dummy coding was used to represent the availability effects and alternative-specific constants. To obtain a parsimonious model, the actual values rather than the categorical levels were used in estimating the choice model. Moreover, to reduce interattribute correlations, deviations from the mean were used in the analysis. Finally, both linear and quadratic effects were estimated to allow for nonlinear effects.

The parameter estimates are presented in Table 2, and the part-worth utility functions are shown in Figure 1. Note that

TABLE 2 Parameter Estimates of the Choice Model

	parameter estimate	standard error	t-value
CAR:			
constant	1.04	0.022	47.66
in vehicle time			
-linear	-0.02	0.002	-10.64
-quadratic	-0.10	0.008	-13.34
In-vehicle delay			
-linear	-0.05	0.002	-26.87
-quadratic	-0.06	0.046	-1.40
walking distance			
-linear	-0.00	0.004	-0.87
-quadratic	-1.88	0.341	-5.50
costs			
-linear	-0.14	0.004	-30.62
-quadratic	-0.83	0.138	-5.99
distance	0.20	0.002	80.74

(continued on next page)

TABLE 2 *(continued)*

	parameter estimate	standard error	t-value
TRAIN:			
constant	0.79	0.026	30.59
in vehicle time			
-linear	-0.08	0.002	-35.71
-quadratic	0.21	0.027	7.63
delay in departure			
-linear	-0.08	0.003	-27.64
-quadratic	0.26	0.163	1.58
in-vehicle delay			
-linear	-0.05	0.004	-10.88
-quadratic	3.17	0.193	16.41
walking distance			
-linear	-0.09	0.003	-31.25
-quadratic	-1.24	0.161	-7.74
costs			
-linear	-0.22	0.010	-21.76
-quadratic	-1.67	0.476	-3.50
comfort			
-linear	0.06	0.003	21.68
-quadratic	-1.17	0.163	-7.18
interchange	-0.06	0.007	-8.05
distance	0.28	0.002	121.15
CARPOOL:			
constant	0.91	0.023	38.63
in vehicle time			
-linear	-0.05	0.002	-27.58
-quadratic	-0.02	0.008	-2.90

(continued on next page)

TABLE 2 (*continued*)

	parameter estimate	standard error	t-value
waiting time			
-linear	-0.06	0.003	-21.18
-quadratic	-0.07	0.156	-0.44
in-vehicle delay			
-linear	-0.05	0.002	-22.36
-quadratic	0.07	0.048	1.51
walking distance			
-linear	-0.00	0.004	-0.88
-quadratic	1.37	0.367	3.74
costs			
-linear	-0.21	0.010	-22.01
-quadratic	6.65	0.591	11.25
driver	-0.02	0.008	-2.64
distance	0.24	0.003	94.54
BUS:			
constant	0.03	0.036	0.92
in vehicle time			
-linear	-0.06	0.001	-44.95
-quadratic	-0.04	0.006	-8.01
delay in departure			
-linear	-0.03	0.004	-6.47
-quadratic	-0.84	0.218	-3.86
in-vehicle delay			
-linear	-0.01	0.003	-3.55
-quadratic	-0.02	0.068	-0.35
walking distance			
-linear	-0.06	0.004	-15.77

(*continued on next page*)

TABLE 2 (*continued*)

	parameter estimate	standard error	t-value
-quadratic	1.80	0.227	7.91
costs			
-linear	-0.39	0.014	-28.12
-quadratic	7.17	1.053	6.81
comfort			
-linear	0.11	0.004	28.02
-quadratic	-1.85	0.218	-8.49
interchange	-0.18	0.010	-19.01
distance	0.26	0.003	84.64

for ease of interpretation of Figure 1, the parameter estimates were rescaled, setting the origin of each part-worth utility scale to zero.

The results obtained for in-vehicle travel time indicate that utility decreases with increasing in-vehicle time, as expected. Apparently, respondents are less concerned about in-vehicle travel time while driving their cars; they are much more sensitive to in-vehicle travel time with respect to the bus and carpooling, and especially with respect to the train.

The parameter estimates for fare/costs indicate that, as expected, respondents are less sensitive to increasing costs with respect to car and carpooling compared with means of public transport. For all these part-worth utilities both the linear and the quadratic terms are significant at conventional probability levels.

The parameters obtained for in-vehicle delay clearly demonstrate that utility for the car and carpooling drops dramatically with increasing delays. Respondents' utility is much less influenced by increasing delays for train and bus. Apparently, delays are already associated with means of public transport, implying that increasing delays affect utility much less. Again, both the linear and the quadratic effects are significant. The utility function for the train is unexpected in that utility increases with substantial delays. It is not readily evident why this effect occurs.

The effects of walking distance indicate that the part-worth utility functions of the two means of public transport decrease with increasing walking distance. The effects are less clear for car and carpooling. This finding suggests that the probability that respondents will choose a means of public transport is affected adversely with increasing walking distance. The slope of the utility function suggests that these effects might be dramatic.

The comfort attribute was used only in connection with the train and the bus. Because it is a multidimensional construct, several indicator variables were used to measure the comfort dimension. Therefore, we first analyzed the contribution of these indicator variables to the overall evaluation of comfort using multiple regression analysis. Next, the effect of comfort on choice probabilities was analyzed. The following equations were estimated:

$$E_{\text{bus}} = 5.12 + 0.71X_{1,\text{bus}} + 0.95X_{2,\text{bus}} + 0.65X_{3,\text{bus}} + \varepsilon_{\text{bus}} \tag{3}$$

and

$$E_{\text{train}} = 6.18 + 0.67X_{1,\text{train}} + 0.63X_{2,\text{train}} + 0.81X_{3,\text{train}} + 0.46X_{4,\text{train}} + \varepsilon_{\text{train}} \tag{4}$$

where

E_{bus} = evaluation of the comfort of the bus;
$X_{1,\text{bus}}$ = -1 if old equipment, 1 if new equipment;
$X_{2,\text{bus}}$ = -1 if no shelter is available at the bus stop, 1 otherwise;
$X_{3,\text{bus}}$ = -1 if there is a 75 percent chance of seat availability, 1 if a seat is available for certain for the entire trip;
ε_{bus} = an error term;
E_{train} = the evaluation of the comfort of the train;
$X_{1,\text{train}}$ = -1 if old equipment, 1 if new equipment;
$X_{2,\text{train}}$ = -1 if no shelter is available at the railway station, 1 otherwise;
$X_{3,\text{train}}$ = -1 if there is a 75 percent chance of seat availability, 1 if a seat is available for certain for the entire trip;
$X_{4,\text{train}}$ = -1 if no refreshments are available on train, 1 otherwise; and
$\varepsilon_{\text{train}}$ = an error term.

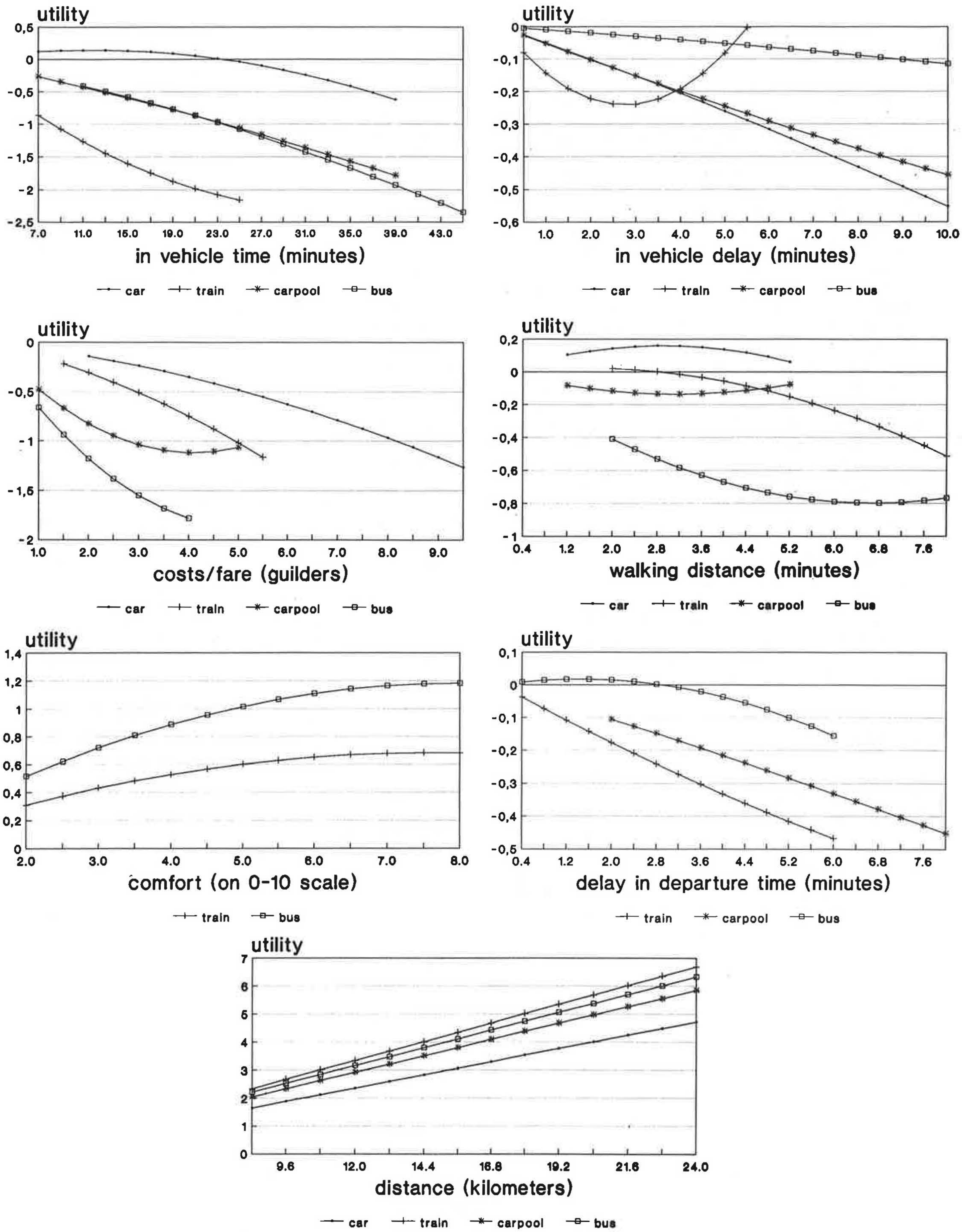

FIGURE 1 **Part-worth utility functions.**

The explained variances were respectively 98 and 99 percent. For the bus, the evaluation of comfort is determined mostly by shelter provision, followed by new equipment and the chance of obtaining a seat. For the train, seat availability is the most important attribute contributing to comfort, followed by new equipment, shelter provision, and refreshments, respectively. The parameters for both the bus and the train were highly significant.

The effect of comfort on utilities demonstrates that the probability of choosing the train or the bus increases with increased evaluation of the comfort dimension. This effect is larger for the bus.

Delay in departure time was incorporated into the utility function of the train, bus, and carpooling only. All three part-worth utility functions decrease with increasing waiting time. Respondents are most sensitive to increasing waiting times for the train, followed by carpooling and bus, respectively.

The utilities for the distance attribute indicate that the utility of all other transport modes via-à-vis the bicycle increases with increasing distance. This effect is largest, as expected, for the train, followed by bus, carpooling, and car.

Interchange was included in the utility function of the two selected means of public transport. Consistent with a priori expectations, both parameter estimates were negative, suggesting that choice probabilities decrease if an interchange is involved. The parameter estimate is higher for the bus. This suggests that respondents are more concerned about an interchange when choosing the bus than when choosing the train.

Finally, a "who drives" variable was included to describe the carpooling alternative. The estimated parameter estimate was -0.022, which reflects that respondents prefer to be a passenger rather than the driver when carpooling.

Availability Effects

These analyses are not different from those typically conducted in stated choice experiments in a transportation context. However, in this study we also estimated availability effects to examine whether the composition of the choice set has any effect on the utility of the travel alternatives. These availability effects depict any departures from the choice probability implied by the IIA-MNL model. The availability effects are presented in Table 3. The diagonal elements are the mode constants, and the other values in each row are the availability effects on the transportation mode as described by the row labels. The availability effects represent changes in the alternative-specific utility functions and are a result of the composition of a choice set. If the MNL holds, implying that the IIA property holds as well, the ratio of choosing a particular travel alternative relative to any other alternative would be independent of choice set composition. Consequently, the availability effects would all be equal to zero (or at least would statistically not be significantly different from zero). Likewise, significant availability effects depict departures from IIA that arise as a result of differences in choice set composition. Except for the relatively small effect of bus on car and the nonsignificant effect of bus on train, all the availability effects are negative and highly significant. This indicates that the transportation modes are to some extent substitutes for each other, but the effects are not symmetric. For example, the availability cross effects of each mode on car are significantly smaller than the corresponding effect of car on each mode. Only the effects of train and carpool are similar in magnitude.

Since we have assumed for practical reasons that the availability by attribute interactions is negligible, the availability cross effects influence only the mode constants in this model. The column ALL PRESENT in Table 3 is just the row sum, and it represents the mode constants in choice sets that have all four modes available. To get the constants in reduced sets, one simply has to sum across columns for those present. There are significant changes in these constants for different subsets.

One way to interpret the availability cross effects is to examine the (relative) changes in mode share and odds ratios for different patterns of availability. Table 4 presents some of these shares and odds assuming that the total contribution to the utility of each mode from the attributes is zero. Table 4 also presents the odds ratios for the MNL model that does not incorporate the effects of differences in choice set composition. Note that Table 4 only displays a few examples of varying choice set composition. The rows in Table 4 represent different choice set compositions, "----" indicating the non-availability of that transport mode. The first five columns represent the market share of each transport mode as predicted by the non-IIA model that includes the estimated availability effects. Thus, the market share of the car is predicted to be equal to 40 percent if all five transport modes are available. The market share of the car increases to 47.5 percent

TABLE 3 Availability Effects (Off-Diagonal Elements) and Mode Constants (Diagonal Elements)

	CAR	TRAIN	CARPOOL	BUS	ALL PRESENT
CAR	1.040	-.114	-.271	.075	.730
TRAIN	-.295	.792	-.427	.005	.075
CARPOOL	-.527	-.412	.909	-.179	-.209
BUS	-.500	-.571	-.463	.033	-1.501

TABLE 4 Mode Shares and Odds Ratios (All Else = Zero)

	NON-IIA-MODEL								MNL-MODEL		
	MODE-SHARES					ODDS-RATIOS			ODDS-RATIOS		
SET	CAR	TRAIN	CPOOL	BUS	BIKE	C/TR	C/CP	TR/CP	C/TR	C/CP	TR/CP
1	.400	.208	.156	.043	.193	1.92	2.56	1.33	1.56	1.68	1.08
2	.388	.216	.195	----[1]	.201	1.80	1.99	1.11	1.56	1.68	1.08
3	.475	.288	----	.062	.175	1.65	----	----	1.56	----	----
4	.470	----	.248	.080	.202	----	1.89	----	----	1.68	----
5	----	.346	.328	.088	.239	----	----	1.05	----	----	1.08
6	.488	.318	----	----	----	1.53	----	----	1.56	----	----
7	.467	----	.317	----	.216	----	1.47	----	----	1.68	----
8	.652	----	----	.134	.214	----	----	----	----	----	----
9	----	.353	.402	----	----	----	----	0.88	----	----	1.08
10	----	.583	----	.154	.263	----	----	----	----	----	----
11	----	----	.557	.175	.268	----	----	----	----	----	----

[1]non-available transport mode

if the carpooling option is not available (Choice Set 3). Columns 6 to 8 represent the odds ratio for, respectively, car-train, car-carpooling, and train-carpooling as predicted by the model that includes the availability effects. Columns 9 to 11 present the corresponding odds ratios for the conventional MNL model. Note that these odds ratios are not influenced by the composition of the choice set (IIA property).

Examination of Table 4 then indicates that the odds ratio for share of car to train changes from 1.92 to 1.53, and car to carpool changes from 2.56 to 1.47 as the availability pattern changes. The odds ratio of train to carpool changes from 1.33 to 0.88. The differential mode shifts in changing availability are thus captured by the cross effects included in the choice model.

The MNL model predicts these odds ratios to be constant, independent of the availability of particular transport modes. A comparison of the ratios for the two models thus provides useful information about mode shifts. For example, the conventional MNL model indicates a slight preference for the train relative to carpooling (odds ratio = 1.08). The ratios obtained for the model that includes the availability effects indicates that this ratio is higher (1.33) if all transport modes are available, but drops to 1.05 if the car is not available. Apparently, therefore, a substantial proportion of commuters says it will switch from car to carpooling rather than choose the train if the car is not available. This ratio drops further to 0.88 if both the car and the bus are not available.

Similar patterns are observed for the odds ratio car-train. If all transport modes are available, this ratio is equal to 1.92. The ratio drops to 1.80 and 1.65 if the bus and carpooling, respectively, are not available. This result indicates that a larger proportion of commuters is predicted to switch to the train rather than to the car if the bus or carpooling are not available. Thus, these odds ratios provide useful information about the competitive structure among the transport modes.

Goodness-of-Fit

The goodness-of-fit of the model was satisfactory. The log likelihood for the null model was −250,716.781; the log likelihood for the estimated model was −204,074.141. The chi-square statistic for the likelihood ratio test was 93,285.28 with 130 degrees of freedom. Thus, the estimated model significantly improves the null model.

The choice model was also estimated without the availability effects. The log likelihood for this case is −205,782.141.

The chi-square statistic for the likelihood ratio test was 3,416.00 with 24 degrees of freedom. Thus, it can be concluded that the inclusion of availability effects significantly improves the performance of the choice model.

CONCLUSION AND DISCUSSION

This paper has focused on the extension of stated choice models in transportation analyses. It has been shown how the MNL model can be extended to include availability effects that represent the effect of the availability or nonavailability of some travel alternative on the utility of remaining alternatives in the choice set. The results of this study suggest that the inclusion of such effects in models of mode choice may considerably improve the predictive success of the choice model. Such effects may account for departures from the IIA property underlying the MNL model.

The ease of including availability effects in a choice model constitutes another advantage of using choice experiments rather than preference experiments typically used in stated preference studies in transportation contexts. As Louviere and Gaeth (*38*) have advocated, the major advantage of choice tasks over rating or ranking tasks is that they focus on choice and hence are probably closer to actual decision making. Moreover, one does not require ad hoc assumptions to relate preferences to choices. Also, choice tasks make it easy to examine much more of the statistical response surface than is usually possible with traditional full-profile stated preference tasks. Finally, as has been illustrated by the present paper, choice experiments can be designed to accommodate a much wider variety of choice models and utility specifications.

The approach outlined in this paper produces models that are compatible with existing discrete choice models. Hence, no specific abilities are required to implement these "availability effects" models. One only needs to know how to design choice experiments that allow availability effects to be estimated. Especially for small-scale problems involving a limited set of attributes, such designs are easy to develop and administer, although choice experiments are more difficult to design than preference designs commonly applied in transportation.

From a substantive viewpoint, the results of this analysis indicate that people's habits to use the car for commuting will be difficult to change. People's preferences for the car only slightly decrease when its attributes deteriorate. Moreover, preferences for modes of public transport drop dramatically with less favorable attribute levels. It implies that the objectives of the transportation planners may be difficult to achieve fully. The values and signs of the availability effects indicate the degree of substitution between transportation modes. These parameters reiterate the strength of the position of the car compared with other transport modes.

We believe that transport mode models incorporating availability effects provide improved information to transportation planners. First, if the results of this application can be replicated in other contexts, models that include availability effects provide better predictions of transport mode share. Second, and perhaps more important, these non-IIA models provide transportation planners with the necessary information that allows them to identify the competitive structure among the transport modes. For example, in the present case the results of the model indicate that policies that aim at substantially reducing the market share of the car by introducing, stimulating, or expanding carpooling schemes or public transportation are not likely to be very successful, because these modes primarily compete among one another rather than with the car. Such additional information would not be provided by conventional MNL or other IIA models, simply because these models are based on the assumption that the utilities and market shares of transport modes are not influenced by the availability of any other transport mode in individuals' choice sets.

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Procedure for the Calibration of a Semicompensatory Mode Choice Model

EIJI KAWAMOTO AND JOSÉ REYNALDO SETTI

A two-step method for the calibration of semicompensatory models is presented. To demonstrate the use of the method, it is applied to a model that represents the process of choosing modes for work trips. The calibration of semicompensatory models, such as the one presented here, is not a trivial process because it involves finding the best set of parameters for two functions while satisfying a series of inequalities. In the example shown here, the inequalities are used to determine whether the modal choice predicted by the model corresponds to the user's choice. The best set of parameters is that corresponding to the fewest differences between the observed and predicted choices. The first stage in the proposed calibration process is a preliminary fitting, which attempts to find the maximum of a deterministic function using a process that resembles the maximum likelihood calibration method. The second stage uses the first parameters determined in the first stage as an initial solution and then tries to find the best fit through an exhaustive search around the initial guess. The justification of this two-step procedure is that the efficiency of the calibration process will be increased, since the technique used in the first stage is faster than that used in the second stage. The proposed procedure ensures that an accurate answer is obtained in a reasonable time while allowing the user to determine the sensitivity of each calibration parameter. The calibrated model was able to correctly predict more than 85 percent of the modal choices observed.

Semicompensatory models make up a class of disaggregated behavior models that may be used to represent the behavior of trip makers who are choosing travel modes and routes. Two other classes of disaggregated behavior models may be identified: compensatory and noncompensatory models. The main difference among these three types of models is the assumption about whether compensations can be made among the attributes that influence the trip maker's decision. The assumption of compensatoriety implies that a high level of satisfaction with one attribute offsets low levels of satisfaction with others (*1*). For example, some models assume that time and cost are compensatory attributes. In terms of the trip maker's perception of a mode's utility, this could mean that the higher cost of a particular mode may be offset by the reduction in travel time obtained when using that mode.

The logit and probit models are two well-known compensatory models. In these models, some amount of utility is associated with each travel mode. The value of the utility of a particular travel mode may be calculated as a function of variables that characterize the socioeconomic situation of homogeneous groups of users, travel costs of the mode, and the mode's attributes (such as comfort, safety, etc.). In a compensatory model, the probability of a user choosing a given mode increases as the relative utility of that mode increases.

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Noncompensatory models assume that choices are made on the basis of attribute-by-attribute comparisons of available alternatives and minimum thresholds of acceptability. Noncompensatory models do not consider trade-offs among attributes (*1*). Examples of noncompensatory models are the lexicographic, the conjunctive, and the disjunctive models (*1–3*), among others. Young has used the elimination-by-aspect technique proposed by Tversky (*3*) in a residential location-choice model, which is a good example of the application of a noncompensatory model (*4*).

Semicompensatory models are based on the assumption that trip makers perceive and distinguish between two categories of utilities: (*a*) an intrinsic utility of a mode and (*b*) the utility of the money spent to use a given mode. The intrinsic utility of a mode is a function of its attributes (such as comfort, safety, travel time, etc.), whereas the utility of the money spent to use this particular mode depends on the trip maker's socioeconomic characteristics. The model also assumes that compensatoriety is only admitted among attributes classified in the same category (such as cost and income, or comfort and travel time) (*5*).

MATHEMATICAL REPRESENTATION OF UTILITIES

In the context where travel is considered an intermediate activity allowing access to other activities, it may be assumed that all trip makers want to minimize travel time, physical effort, and other inherent effects of locomotion. Therefore, the intrinsic utility of a mode increases as its level of comfort and rapidity increase—where rapidity is defined as the ratio between the origin-to-destination straight-line distance, raised to a certain exponent, and the travel time, raised to another exponent.

The semicompensatory structure assumes that an individual's decision about the use of the mode perceived as having the greatest intrinsic utility depends on the individual's perception of the utility of the amount of money required to use that particular mode, which is a function of the out-of-pocket cost associated with the mode and of socioeconomic factors such as income and number of dependents. If the intrinsic utility of a given mode is greater than the utility of its out-of-pocket cost, that mode will be chosen for the trip; otherwise, this model will be considered too expensive, and the second-best alternative is taken into consideration in a similar way.

The intrinsic utility of a mode is expressed as a function of the following attributes: travel time, amount of physical effort required (a proxy for comfort), and straight-line distance between origin and destination. The utility of the money spent for using a mode is described as a function of out-of-pocket cost, household income, and number of dependents.

These two utility functions have a multiplicative form, because previous studies have shown the adequacy of the multiplicative rule in representing the perception of a multiattribute stimulus (*6*) and human judgment concerning travel behavior (*5*). In other words, the perception of a set of attributes by a certain user may be represented by a multiplicative model in terms of actually measured values and not perceived values. For instance, the model uses "real" data for travel time or distance instead of values obtained from answers to questionnaires—which are affected by the respondent's perception. Thus, the intrinsic utility of Travel Mode m is given by the expression

$$I_m = \alpha_0 \cdot D^{\alpha_1} \cdot T_m^{\alpha_2} \cdot E_m^{\alpha_3} \tag{1}$$

where

I_m = intrinsic utility of Mode m;
D = straight-line distance between origin and destination;
T_m = travel time by Mode m;
E_m = physical effort required for traveling by Mode m, defined as the amount of bodily energy spent by the user when traveling by Mode m, given the travel time; and
α_i = calibration constants, which transform objective measurements into perceived values.

Note that the level of comfort is taken into account by the model insofar as comfort is the inverse of physical energy, E, raised to some power.

The second equation, for the utility of the money required to use Mode m, is given by

$$S_m = \beta_0 \cdot P_m^{\beta_1} \cdot R^{\beta_2} \cdot N^{\beta_3} \tag{2}$$

where

S_m = utility of the money required to use Mode m;
P_m = out-of-pocket cost for using Mode m;
R = household income;
N = number of people depending on the household income; and
β_i = calibration constants.

A trip maker j chooses the mode for a trip by first ranking the available modes according to their intrinsic utilities: $I_p^j > I_q^j > I_r^j > \ldots$. The intrinsic utility for the most preferred mode (Mode p) is then compared with the utility of the money required to use that mode: if $I_p^j > S_p^j$, then Mode p is chosen; otherwise, the second-highest-ranked mode is considered. Therefore, Mode q is chosen if $I_q^j > S_q^j$. If $I_q^j < S_q^j$, the process is repeated until a mode whose intrinsic utility is higher than the money utility is found.

CALIBRATION OF THE SEMICOMPENSATORY MODEL

The calibration of compensatory disaggregated behavior models uses the probability that an individual belonging to a homogeneous group will choose a certain alternative, measured as the frequency of occurrence of each alternative. The main difficulty in calibration of semicompensatory models is the lack of a measurable variable linked directly to the choice of an alternative (e.g., the probability of choosing private car). However, this does not rule out probabilistic approaches to semicompensatory models—Kawamoto has proposed a probabilistic structure for the semicompensatory model (*7*). The calibration of such a model would require observations of the frequency of mode utilization for homogeneous groups of users.

The semicompensatory model, as proposed by Kawamoto (*5*), should be calibrated for each person in the data set through the comparison of observed and predicted choices. This is because it is almost impossible to determine individual propensities of choosing an alternative from observed individual choices. Although this deterministic approach may cause some operational difficulties, it allows for a better understanding of the process of mode selection because the underlying assumptions about the structure of the trip maker's behavior are explicit.

The multiple regression approach for the calibration of the model was discarded because of potential problems in the collection of accurate data. To use a multiple regression model, it would be necessary to know the points of indifference between the two utilities. Therefore, each subject interviewed would be required to state at least one combination of attributes of a mode that would make that mode's intrinsic utility equivalent to the utility of the money required to use it (for instance, the price of fuel that would cause the trip maker to stop using a car, and so on). Responses to this type of question are usually not reliable because the subject must think about hypothetical situations and not about real ones. Furthermore, it would be necessary to assume that these stated combinations of attributes are really representative of the points of indifference between utilities.

Linear programming was also considered for the calibration of the model. The objective function would be some function that would reflect the difference between the predicted and observed choices, subject to the restrictions represented by the inequalities, which would also need to be linearized. The main problem with this approach is that a solution (or solutions) for the problem would have to satisfy all restrictions, a condition that is equivalent to correctly predicting all observed choices and that is very unlikely to occur.

To avoid such pitfalls, Kawamoto has proposed that the best way to calibrate the model would be to use data on choices that people have actually made, given the available travel modes (*8*). Each subject interviewed is asked to rank the available alternatives. It is then possible to find the rank of the mode each person in the sample actually used for his or her trip. For instance, if an individual has three alternative modes available for a trip, the person can rank the modes according to their perceived intrinsic utilities as well as indicating which mode is actually used. Hence, it can be determined whether the mode used is considered best, second-best, or third-best.

If the chosen alternative is the best of the three available, the value of its intrinsic utility (I_1) must not only be the greatest among the three alternatives ($I_1 > I_2 > I_3$, where I_2 and I_3 are the intrinsic utilities of the modes ranked second and third, respectively) but the intrinsic utility of the selected mode (the one ranked best) must also be greater than the utility of the amount corresponding to the out-of-pocket cost of this alternative ($I_1 > S_1$).

If the alternative used is the second-best, the following inequalities are valid:

$$I_1 > I_2 > I_3$$

$$I_1 < S_1$$

$$I_2 > S_2$$

where S_2 is the utility of the amount corresponding to the out-of-pocket cost for the alternative ranked second. Finally, if the individual can only use the third-best alternative, the values of the intrinsic utilities must satisfy the following inequalities:

$$I_1 > I_2 > I_3$$

$$I_1 < S_1$$

$$I_2 < S_2$$

$$I_3 > S_3$$

The number of inequalities that must be verified for a particular trip maker depends on the number of alternatives and the rank of the alternative selected.

The first stage in the two-stage calibration procedure tries to find values for the calibration constants α_i and β_i such that most of the preceding inequalities are satisfied for the largest number of subjects in the sample. The procedure adopted in the first stage resembles the maximum likelihood method, although the utility functions used are deterministic. The second stage uses the results of the first stage as an initial guess and tries, through exhaustive search, to find regions of optimal values around this starting point.

First Stage

The calibration of the semicompensatory model consists of finding a set of parameters that make the previously defined set of inequalities true for the maximum number of individuals in the calibration data set. The first step in the proposed two-stage calibration technique tries to find an initial set of parameters V_0 quickly through a process that resembles the maximum likelihood calibration technique, in spite of the deterministic nature of the functions used.

Kawamoto (*8*) has used a technique for the calibration of semicompensatory models that involves two functions. The first function, $f_{jk}(V_l)$, verifies whether the kth inequality is true for User j, given a parameter vector V_l:

$$f_{jk}(V_l) = \frac{e^{U_x}}{e^{U_x} + e^{U_y}} = \frac{1}{1 + e^{U_y - U_x}} \tag{3}$$

where U_x and U_y are utilities and e is a constant, usually the base of natural logarithms, 2.718 . . . .

This function ranges from 0 to 1: if $f_{jk} > 0.5$, then $U_y < U_x$; if $f_{jk} < 0.5$, then $U_y > U_x$. For each user j there is a corresponding number of inequalities t_j to be checked, which depends on the number of alternatives and on the rank of the selected alternative.

A second function, $g(V_l)$, is defined for a vector of calibration parameters V_l as follows:

$$g(V_l) = \prod_{j=1}^{n} \prod_{k=1}^{t_j} f_{jk} \tag{4}$$

where

f_{jk} = function indicating whether a particular inequality is true (Equation 3) for User j,
n = number of subjects in the sample used for calibration of the model, and
t_j = number of inequalities defined for User j.

This function is submitted to a maximization procedure to find the best set of calibration exponents.

Despite its computational efficiency, three problems are associated with this approach:

1. The function f_{jk} (Equation 3) used to check whether an inequality is true may distort the results because the results of the test are weighted. For instance, consider two situations, one where $f = 0.9$ and another where $f = 0.7$. Both represent situations where the inequalities are true ($f > 0.5$), but higher values of f will generate higher values of g, distorting the results.
2. The maximization of Function g corresponds to the maximization of the number of true inequalities. Unfortunately, the largest number of true inequalities may not correspond to the minimum difference between predicted and observed choices.
3. Although the maximization of Function g produces a vector of calibration parameters V_0, there is no warranty that the minimum difference between predicted and observed choices corresponds to only one vector, V_0. In fact, given the discrete nature of the objective function (number of correctly predicted choices), there may be several vectors that can yield the same degree of precision.

The first stage in the calibration process presented here is largely based on Kawamoto's 1989 procedure. A critical change is that the function f_{jk} is modified to avoid the introduction of distortions because of the weighting of the results of the inequality checks (Item 1). Thus, f_{jk} has been changed to

$$f_{jk} = \begin{cases} 1.0 & \text{if the inequality is true} \\ 0.9 & \text{otherwise} \end{cases} \tag{5}$$

This change eliminates the first of the problems with the former approach. To minimize the influence of the other two problems, the new process includes a second stage, which uses the calibration vector V_0 determined in this first step as a starting point in the search for the best exponents for the utility expressions (described by Equations 1 and 2).

Second Stage

The procedure adopted for the second stage needs an initial "guess" for the calibration parameters—here, the exponents obtained by the first stage. Through an exhaustive search procedure, small variations are introduced in these initial values, and the number of correctly predicted choices is calculated for each variation in each exponent. The number of correctly predicted choices is determined through the computation of the utility functions values for each subject in the sample; if all inequalities for each subject are true, the predicted choice is correct.

This procedure is computationally not efficient. For instance, if the search is carried out for 10 values around the initial guess, there are 10^7 combinations of calibration parameters to be verified, and the number of correctly predicted choices has to be determined for each of these 10^7 vectors. The computational inefficiency of this procedure rules out the possibility of its sole use unless enough computing resources are available.

DATA COLLECTION AND MODEL CALIBRATION RESULTS

Data Collection

The data used to demonstrate the model calibration procedure proposed here were collected in two medium-sized cities in Brazil (São Carlos and Campinas) in May 1989. Both cities are in the state of São Paulo in the southern region of the country. The population of Campinas is roughly 1 million; Campinas is 95 km northwest of the city of São Paulo. São Carlos is about 230 km northwest of São Paulo; the city's population is 160,000. Both Campinas and São Carlos are fairly industrialized and are major urban centers in the state.

The method adopted for the data collection was to interview subjects at their workplaces. In São Carlos, interviews were carried out at the campus of the University of São Paulo (USP). In Campinas, data were collected at the Highway State Department Regional Headquarters (HSD). The choice of sites was based on their availability (the interviewers were known by the workers) and the fact that the reliability of certain responses (such as trip length, travel time, etc.) could be determined.

The inclusion of data from Campinas was meant to avoid calibration based solely on short trips. Travel distances for USP workers range from 0.5 to 5 km, with a mean trip length of 2 km; most trip lengths for HSD workers range from 5 to 10 km, with values as high as 18 km. Although these distances may seem short to the North American reader, any trip longer than 15 km is usually considered to be a long work trip for most Brazilians.

The data collected in the interviews included residential address, workplace address, main mode used in the work trip, family income, work trip length, number of people dependent on the family income, travel time, out-of-pocket cost of the work trip, and how the subject would rank the available modes if no expenses were associated with their use. The interviewees were asked to give their best estimates for travel time, distance and cost—the objective was to find "real" rather than subjective values for these variables. The responses to these items in the questionnaire were later checked against reliably calculated values; whenever any significant inaccuracies were noticed in the subject's answers, the calculated values replaced the subject's estimates. The use of this procedure can be justified by the multiplicative form of the model, which has been proved to be able to transform objective measured values into perceived magnitudes by Stevens (*9*) and Louviere (*6*), among others. The reader is referred to these authors for further details on multiplicative models.

The sample consisted of 95 interviewees, 45 in Campinas and 50 in São Carlos. Data related to modes not actually used by the subjects were determined from other sources of information, such as observed bus and car speeds, bus headways and routes, and so forth. This procedure was adopted to avoid errors introduced from any bias toward a particular mode—subjects may not be able to give an accurate assessment of the attributes of the modes they do not use.

The estimate of the out-of-pocket cost associated with use of a private car was made assuming that (*a*) the only cost actually perceived is the fuel cost, (*b*) the average gas mileage under normal urban traffic conditions is 7 km/L of fuel, and (*c*) the morning warm-up cycle consumes 0.3 L of fuel. Travel time for private car users was estimated considering that (*a*) the average morning warm-up cycle for an average car is 5 min (since a large number of cars are fitted with ethanol-powered engines whose warm-up cycle is longer than that of gas-powered engines), and (*b*) the average speed of a car, under normal traffic conditions, is 30 km/hr.

Travel time for bus transit users was calculated on the basis of the following assumptions: (*a*) the average speed for buses is 15 km/hr under normal traffic conditions and (*b*) the total travel time for bus users is given by the sum of the time to walk from home to the bus stop, the wait at the bus stop (half the average headway), the in-vehicle time, and the time to walk from the bus stop to the workplace. Travel time associated with walking was calculated assuming that the average walking speed is 5 km/hr.

Although there may be some degree of correlation between travel time and out-of-pocket cost for automobile trips of these lengths, there is no such correlation between travel time and travel cost for the other two modes—transit fares are uniform for all routes in both cities, and the out-of-pocket cost for walking is nil. Therefore, it may be assumed that the effects of the correlation between travel time and cost are negligible considering that (*a*) the variable travel time is used in the intrinsic utility model (Equation 1) and the variable cost is used in the monetary utility model (Equation 2), and (*b*) that the data set used includes not only drivers but also walkers and public transit riders.

Finally, Table 1 gives the level of physical effort associated with the use of each travel mode (*10*). The physical effort used during a bus trip was estimated as the weighted average of the energy requirements for walking to and from the bus stop, standing at the stop, and riding a vehicle as a passenger.

TABLE 1 Physical Effort Requirements by Mode (*10*)

Mode	Energy expenditure (kcal/min)
Driving	2.8
Walking	4.5
Riding a bus	2.5

Model Calibration Results

The first stage produced the following calibration parameters:

$$I_m = 100D^{1.03}T_m^{-0.60}E_m^{-1.61} \quad (6)$$

$$S_m = 3{,}680P_m^{1.05}R^{-0.82}N^{0.35} \quad (7)$$

where distance is expressed in kilometers; travel time in minutes; energy consumption in kilocalories per minute; and out-of-pocket cost and household income in American dollars. This model was able to correctly predict the choice of 85.3 percent of the subjects in the data set (81 out of 95 cases). The signs of the calibration parameters obtained are consistent with their expected signs. For instance, the greater the travel distance, the greater the utility of a mode, provided time and physical effort are fixed. If a mode allows a longer distance to be traveled with the same time and energy expenditures as other modes, this mode is clearly superior. Similarly, the utility of a given amount of money, perceived by a person whose family income is fixed, increases as family size increases.

Although it is hard to comment on the absolute magnitude of the exponents, it is possible to verify that the relative magnitude of the calibration parameters is also consistent with the observed behavior. For instance, the interviews indicate that the most important attribute in the perception of a mode's utility is its level of comfort. The calibrated model is consistent with this observation: the variable with the highest exponent is physical effort, a proxy variable for level of comfort. Similarly, in the equation for the perception of the utility of an amount of money, the order of the attributes, in terms of their importance, is the magnitude of the amount itself, family income, and family size. This, also, is consistent with the observations.

The second stage was conceived with the main purpose of improving the initial answer through an exhaustive search procedure. Yet, the number of correctly predicted choices did not increase from the first to the second stage. Instead of increasing the accuracy of forecast, the second step indicated that there are many combinations of exponents that can produce the same number of correctly predicted choices. Table 2 gives exponents of eight models and their averages—the constant α_0 is assumed to equal 100. Any of these eight models, as well as the model with the average exponents, is able to correctly forecast the choices of 81 of the 95 subjects interviewed. If smaller increments were used in the exhaustive search, other models would be found.

TABLE 2 Calibration Parameters

	Calibration parameters							
Model	α_0	β_0	α_1	β_1	α_2	β_2	α_3	β_3
1	100	3400	0.990	1.110	-0.620	-0.820	-1.610	0.340
2	100	3400	0.990	1.110	-0.620	-0.820	-1.610	0.360
3	100	3500	0.990	1.110	-0.600	-0.820	-1.630	0.340
4	100	3500	0.990	1.110	-0.600	-0.820	-1.630	0.360
5	100	3500	0.990	1.110	-0.600	-0.820	-1.630	0.380
6	100	3600	0.990	1.110	-0.620	-0.840	-1.670	0.340
7	100	3600	0.990	1.110	-0.620	-0.840	-1.670	0.360
8	100	3700	0.990	1.110	-0.620	-0.840	-1.630	0.360
mean	–[a]	3525	0.990	1.110	-0.613	-0.827	-1.635	0.355
σ	–	103.510	0.000	0.000	0.010	0.010	0.023	0.014

[a] α_0 was assumed to be a constant.

The existence of multiple solutions able to produce the same number of correctly predicted choices is due to the discrete character of the objective function, the number of correctly forecasted choices. Although small variations in the calibration parameters (as given in Table 2) produce the same number of correct predictions, the set of subjects whose choice was correctly forecast is not the same for all the models. There may be a subset of subjects whose choice is correctly predicted by all models, but there may also be some subjects whose choice is correctly predicted by one model and not by the others. In fact, there is a group of 77 people whose choice is always correctly forecast by the models given in Table 2; the differences found among the results produced by the eight models are due exclusively to the composition of the remaining subset (four people). Therefore, the semicompensatory model's results are stable for the majority of the people in the data set used.

CONCLUSIONS

The two-stage calibration procedure presented here was shown to be a feasible way for calibrating a semicompensatory mode choice model. The calibrated model is able to correctly predict more than 85 percent of the observed choices. A particular characteristic of the proposed calibration procedure is that it is able to come up with many models, each having the same degree of accuracy as measured by the number of correctly predicted choices. This characteristic is due to the discrete nature of the objective function.

Because of the limitations of the data set used, it is not possible to say that the utility functions obtained in the calibration procedure represent the users' perceptions, although the authors believe that the exponents obtained are good approximations to the real ones. Larger data sets would improve the accuracy of the calibration, but larger data sets would also need longer processing times. To analyze the spatial and temporal transferability of the calibrated model, it would be necessary to calibrate the model using data sets collected in different regions and countries.

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Daily Variability of Route and Trip Scheduling Decisions for the Evening Commute

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The day-to-day variation of individual trip scheduling and route decisions for the evening commute is addressed on the basis of detailed 2-week diaries of actual commuting trips completed by a sample of automobile commuters in Austin, Texas. The potential impact of using alternative measures of variability in the context of the daily commute is illustrated by comparing a "day-to-day" with a "deviation from normal" approach to individual switching behavior. Models are presented to relate observed route and departure time switching patterns to the commuters' characteristics, such as workplace conditions, socioeconomic attributes, and traffic system characteristics. About 39 percent of all reported evening commutes contained at least one intermediate stop, highlighting the importance of trip linking in commuting behavior. These multipurpose trips are shown to significantly influence the route and joint switching behavior of the commuters. The emerging picture of evening commuting habits clearly suggests high variability of the daily departure time from work, in part due to the trip-scheduling flexibility associated with this trip.

The trip decisions made by daily work commuters have a determining effect on urban traffic congestion and associated air quality. The effectiveness of several important approaches and policies aimed at alleviating these problems depends on commuters' responses to those measures and thus requires an understanding of commuter behavior processes and the development of predictive models of these processes. Such approaches include peak spreading through flexible hours, trip reduction through telecommuting, and traffic management through the use of origin-based and in-vehicle real-time information (which falls under the IVHS umbrella).

In the past few years, commuter behavior has been the subject of several studies, but with a rather limited scope. Most of these have focused on the morning home-to-work journey. Much less attention has been devoted to the evening return-home commute, which is a major factor in the formation of congestion during the evening peak period. Mannering and Hamed (*1,2*) have studied the timing of the return-home trip for a small sample of commuters in the Seattle area as well as the activity patterns of workers at the end of the work day (*3*). As limited as these studies have been, they still provide useful insights into this important aspect of commuter behavior, pointing in particular to the flexibility available to commuters in such decisions and the sociodemographic factors influencing this behavior.

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There appear to be virtually no published studies on the daily variability of actual trip timing and route choice decisions made by commuters with regard to their evening return-home commute. These aspects are significant for the following reasons: (*a*) there appears to be good potential for influencing such decisions to improve traffic conditions and air quality, given the apparently greater degree of flexibility that workers have in the evening; (*b*) such influence is likely to be achievable through emerging information technologies; (*c*) commuting trip patterns are generally assumed to be among the most temporally stable trip purposes, and the extent of their daily variability is not sufficiently documented; and (*d*) actual path choice decisions of individual commuters have not been documented in the past, certainly not from day to day.

A major difficulty in studying the preceding aspects pertains to the observation of the actual behavior of commuters over time, especially in terms of specifying the actual paths traveled by commuters through the network. In previous work, Mahmassani and coworkers have investigated these decisions primarily through laboratorylike experiments under controlled conditions (*4–6*). In this study, commuter decisions are observed in an uncontrolled environment, in which they are influenced by a multitude of interacting factors, including trip chaining considerations, which were controlled for in the laboratory experiments. The study is based on a detailed 2-week diary of such decisions.

DESCRIPTION OF SURVEY AND CHARACTERISTICS OF PARTICIPANTS

This study is based on a survey of a sample of commuters in the northwest section of Austin, Texas, a moderately affluent suburban residential area adjacent to major technology-based manufacturing and R&D activities, with commuting patterns that include a large inter- and intrasuburb component. The survey was conducted in two stages: an initial short screening survey sent to 3,000 randomly selected households (all daily work commuters in a household were asked to complete separate survey forms), and a detailed trip diary. The first mailing was a short, one-page questionnaire on general commuting habits and tendencies. The second stage consisted of a 2-week work trip diary sent to 331 selected first phase respondents (all automobile commuters). A complete description of the first-stage effort, which yielded 624 (in some cases partially) completed surveys, can be found in Caplice (*7*). Detailed analyses including the estimation of switching models completed in the first stage of the survey are presented in previous work (*7,8*). These analyses are based on static stated responses regarding route and departure time switching in general. Data of this nature have well-known limitations with regard to correspondence with actual behavior.

These limitations were addressed in the second stage of the survey, which consisted of very detailed diaries of actual departure and arrival times, street-by-street route descriptions, and intermediate stop (trip-chaining) information for both the morning and evening commuting trips for each day of the 2-week period. In addition, the survey asked for the official work start time for the morning commute and the official work end time and target arrival time at home (if any) for the evening commute. This information can be used to measure daily travel time, schedule delay, and departure time switching. The routes were coded using a graph representation of the 1985 network of the Austin area (obtained from the Planning Division of the Texas State Department of Highways and Public Transportation). More details on the format of the second-stage trip diaries can be found in Hatcher (*9*). A total of 164 participants completed at least 3 days of the diary. The analysis was limited to those trips that begin and end with the usual work and home locations (for each commuter), resulting in 1,312 usable work-to-home trips.

General commuting information for the diary participants is given in Table 1. The majority are males, are between the ages of 30 and 60, and own their place of residence. They prefer to arrive about 15 min on the average before their official work start time. About 43 percent of the commuters reported tolerance to lateness at the workplace in excess of 5 min. The average travel time from work to home for the commuters on days with no intervening stops is 23.6 min. Comparisons of the distributions of the variables in Table 1 with those in the first-stage survey indicate that the diary participants are representative of all first-stage respondents.

TRIP-CHAINING BEHAVIOR

The variability of trip-timing and route choice decisions cannot be properly analyzed without considering the associated trip-linking behavior of the commuters. During-work trip chains (beginning and ending at work) and home-based trip chains (beginning and ending at home), not recorded in our travel diaries, have been addressed by other authors, such as Kitamura et al. (*10*). The trip-chaining behavior addressed in this paper corresponds to the critical evening commuting periods. Since only after-work paths are considered, all trips begin at work and end at home. These trips may or may not have intermediate stops.

Diary information available for each stop includes location, purpose, arrival time, and departure time. Stop locations were coded to the nearest node (or centroid) of the Austin network. Twenty-one initial stop purposes were coded, then subsequently combined into five major activity groups for analysis:

- Serve passenger,
- Personal business,
- Food/recreational/social,
- Shopping, and
- Other (includes meetings, medical appointments, and work-related errands).

A total of 516 (39.3 percent) out of 1,312 commutes had one or more stops. About 11 percent of all evening trips had two or more stops. In total, 719 after-work stops were documented in the diaries. The relative frequency breakdown of activity types of these stops is as follows: personal business, 24.2 percent; shopping, 23.8 percent; food/social/recreational, 19.9 percent; serve passenger, 16.8 percent; and other, 15.3 percent.

For each commuter, a stops ratio was calculated by dividing the number of trips with stops by the total number of trips reported. For example, a stops ratio of 0.5 indicates that the commuter stopped on exactly half of the evening commutes. Only about 14 percent of the commuters did not report making a stop on any of their commutes during the survey period (stops ratio = 0.0). At the other extreme, about 5 percent of them made stops on every trip (stops ratio = 1.0). A wide spread of values was observed for the stops ratio, a reflection

TABLE 1 Characteristics of the 164 Diary Participants[a]

Average Usable Trips per Commuter (164)		8.00 (10 is maximum)
Average Actual PM Travel Time (No Stops) (156)		23.6 minutes
Type of Work Hours (164)	Regular Work Hours	84.8%
	Flexible Work Hours	10.3%
	Scheduled Shift Work	4.3%
	Other	0.6%
Average Early Preferred Arrival Time at the Work Place (159)		15.6 min
Percentage with Lateness Tolerance (>5 min) at Work (162)		42.6%
Commuters Listening to Radio Traffic Reports (164)		67.7%
Gender (male) (164)		67.7%
Age (164)	Under 18	0.0%
	18-29	4.3%
	30-44	48.8%
	45-60	42.6%
	over 60	4.3%
Commuters Renting Their Residence (164)		8.5%

[a] Sample size of diary participants for each response is in parentheses.

of both different commuter trip-linking habits and daily variability in the commuting pattern of each participant (both inter- and intrapersonal variability).

Some workers routinely make a stop during their evening commute; for example, a parent may pick up a child at school or a day care center on the way home from work. The behavior of routine stoppers may vary significantly from that exhibited by those making nonroutine stops. With this in mind, the set of all stops was separated into routine and nonroutine stops. Though several definitions are possible, a stop was classified as routine if it is made (for a given commuter) (*a*) at the same location and (*b*) with a frequency of at least three in five commuting trips (the location had to be visited at least three times to be considered). This definition is based on the location and not the purpose of the stops, although most stops at a given location will have the same purpose. Huff and Hanson (*11*) used "core stops" to describe a similar phenomenon and studied the effect of three core-stop definitions.

By our definition, 115 (15.9 percent) of the evening stops are routine. Furthermore, 21.7 percent of the trips with stops contained routine stops. Sixteen commuters (9.7 percent of all commuters, 11.3 percent of those with stops) had at least one routine stop (one had two). As expected, the majority of these routine stops are made to serve a passenger (62.6 percent of all routine stops). More detail on the observed trip-chaining characteristics can be found in related work (*9,12*).

TRIP-SCHEDULING AND ROUTE DECISION VARIABILITY

Critical to the modeling of commuter behavior are the mechanisms by which users choose routes and departure times, and the factors that determine the variability of these decisions from day to day. In this section, we analyze the departure times and street paths taken by each commuter for the evening work journey over the 2-week survey period.

A departure time switch can be defined in several ways. In previous work, Mahmassani et al. (*4*) defined a departure time switch in a dynamically evolving context as a day-to-day change of a certain magnitude (e.g., 5 min). Mannering (*13*) described a time change as a deviation from a "normal" departure time with the "intent of avoiding traffic congestion and/or decreasing travel time." In this study, we compare alternate switching definitions and thresholds and illustrate the dependence of certain behavioral conclusions on these definitional issues. Two ways of capturing departure time switching behavior are discussed here: (*a*) switching from a commuter's median departure time (median switching) and (*b*) switching from a user's previous day's departure time (day-to-day switching). Median switching is intended to capture deviations from a usual daily routine. The median was chosen for this purpose instead of the mean to avoid the undue influence of outliers in a commuter diary. By the day-to-day definition, the current day is considered a switch from the previous day if the absolute difference between their respective departure times exceeds (or meets) some minimum threshold. This definition is important in modeling the day-to-day evolution of flows in the commuting system and dynamic equilibrium processes (*14*).

We also explore two definitions of a route switch. First, we define a mode route switch as a deviation from the normal or mode (most frequently used) network route (a route is a unique sequence of network nodes), in which the commuter follows a "different than usual" set of nodes to arrive at work. This criterion recognizes the observed dominance of one route over all others for most commuters. Second, we define a day-to-day route switch as a route that is different from the previous day's route. To minimize capturing trivial route switches, minor deviations around the trip ends (neighborhood streets) or a network node (e.g., a minor cutoff street to avoid an intersection) are not considered route switches.

Results of the departure time and route switching analysis are presented in Table 2. Departure time switching thresholds of 3, 5, and 10 min are considered: deviations (absolute value) greater than or equal to the thresholds are considered switches. We attempt to control for departure time switching that is directly induced by a different work end time by limiting the analysis to commuter trips with the same work end time (for median switching, Definition 2) or trips in which the work end time is within 5 min of the previous work end time (for day-to-day switching, Definition 4).

Table 2 clearly indicates that workers engage in a substantial amount of evening departure time switching. As expected, the day-to-day definition results in a higher percentage of switches than does the median definition. In fact, additional analysis indicates that more than 40 percent of these commutes are 20-min day-to-day switches. The 3-min threshold tends to confound what may be considered "noise" with actual intended changes in departure time. The 5- and 10-min thresholds appear to be the most plausible for the purpose of this study. These two thresholds are also appealing because they correspond better with clock times than the 3-min threshold.

Route switching is not as frequent as departure time changing for the evening commutes. Less than two in five trips use a nonmode (i.e., other than the most frequent) route, suggesting the existence of a usual route for most commuters. When trips with stops are excluded from the data (Definition 2), nonmode trips account for only 12.7 percent of the remaining trips. Again, the day-to-day definition captures more switching than other definitions. The lower frequency of route switching relative to departure time switching is consistent with the results of stated preference experiments under simulated traffic conditions (*5*).

A joint switch consists of both a departure time and route switch on a given trip. Two definitions of joint switching are explored (corresponding to the definitions for the individual choice dimensions). First, a median/mode joint switch is defined as a median departure time switch together with a mode (all days) route switch. Second, a day-to-day joint switch is defined as a day-to-day departure time switch together with a day-to-day route switch. As shown, a significant amount of joint switching occurs during the evening commute. More than two in five evening commutes are joint 5-min day-to-day switches.

This variability at the individual level suggests a high potential for variable aggregate temporal and spatial demand patterns during the evening peak period. In addition, the sensitivity of behavioral conclusions to definitional and measurement issues is highlighted by these results. Note that our

TABLE 2 Results of Departure Time and Route Switching Analysis

Percent of Trips that are Switches

Departure Time Switching

Definition	Switch Threshold (minutes) 3	5	10	Number of Trips
1. median	70.3	63.0	50.0	1298
2. median (WEC[a])	63.8	55.7	40.8	961
3. day-to-day	85.7	79.8	65.8	1136
4. day-to-day (WEC)	81.9	74.6	58.8	878

Route Switching

Definition	% Switches	Number of Trips
1. mode (all days)	36.1	1312
2. mode (days with no stops only)[b]	12.7	796
3. day-to-day	53.2	1148

Joint Switching

Definition	Departure Time Switch Threshold (minutes) 3	5	10	Number of Trips
1. median/mode[c]	26.7	24.3	19.3	1298
2. median/mode (WEC)	24.8	22.3	16.9	961
3. day-to-day[d]	46.6	43.9	37.6	1136
4. day-to-day (WEC)	44.9	41.6	34.6	878

[a] WEC= work end controlled
[b] Mode routes were redefined by selecting only days with no stops.
[c] Median definition used for departure time switch, mode (all days) definition used for route switch.
[d] Day-to-day definition used for departure time and route switch.

results correspond to actual decisions observed in the network regardless of the underlying motive. As such, these results provide a characterization of the natural variability of commuter decisions in a real system.

Consistent with the stated preference experiments of Mahmassani and Stephan (*5*), departure time and route switching decisions are not independent of each other, as confirmed by chi-squared tests for the various definitions. The tests confirm that the dependence increases as the departure time switch threshold increases (as reflected in higher computer chi-squared values).

The values in Table 2 do not highlight differences across individuals, especially since different commuters reported different numbers of trips during the survey period. Switching ratios were obtained by dividing the number of switches by the number of possible switches, for each individual, for each departure time and route switching definition (a ratio of 1.0 indicates a switch on every possible day). Figure 1 shows the differences between departure time switching definitions by showing the cumulative relative frequency distributions (across commuters) of the alternative departure time switching ratios (for controlled work end times). For example, the percentage of workers never switching departure time is approximately 19 percent according to the 10-min median definition, 11 percent by the 10-min day-to-day definition, 5 percent by the 5-min median definition, or 3 percent by the 5-min day-to-day definition. These discrepancies underscore the importance of definitional issues with regard to departure time switching. According to the conservative 10-min median definition, 37 percent had a switch ratio of 0.5 or higher. The emerging picture of evening commuting habits clearly suggests high variability of the daily departure time from work.

The cumulative relative frequency distributions of the three route switching ratios are also shown in Figure 1. When all days are analyzed, only 15.5 percent of the users never switch routes during the p.m. commute. About 28.6 percent of commuters switch from this mode with a frequency of more than 1 in 2 days. Significantly less switching relative to the mode route occurs if only no-stop routes are considered, because 64.3 percent of the users never switch routes under these circumstances, and only 7.9 percent have a switch ratio greater than 0.5. Under the day-to-day definition, 52.9 percent of commuters have a switch ratio greater than 0.5. Clearly, the need to link one or more activities along the commute influences path selection and causes a substantial amount of route switching, even for those who would not change routes otherwise. The variability in switching behavior exhibited by the commuters provided the impetus for the modeling efforts presented in the next section.

SWITCHING FREQUENCY MODELS

Insights into the factors that influence route and departure time switching behavior in connection with the evening commute would contribute to the ability to develop and analyze

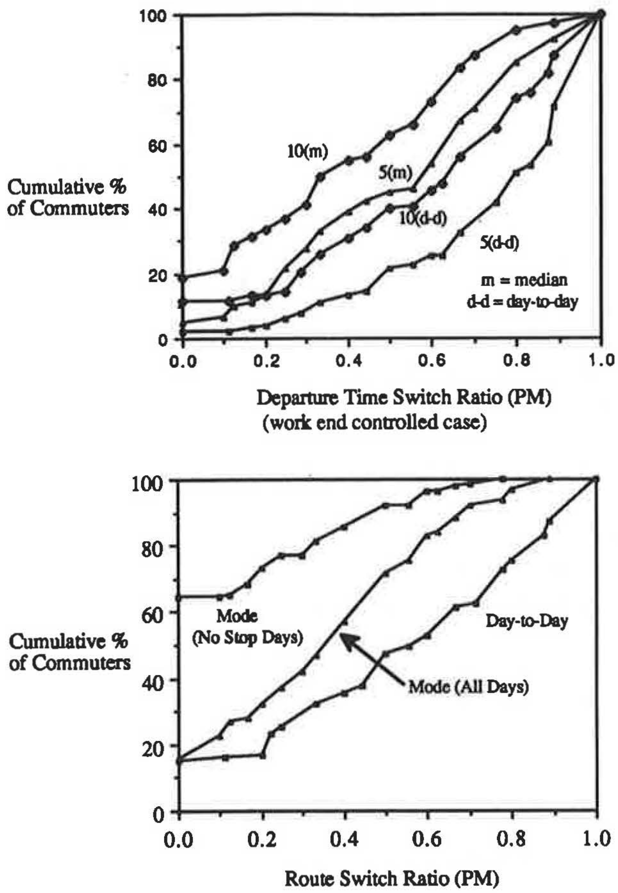

FIGURE 1 Cumulative distributions of (*top*) departure time and (*bottom*) route switching ratios, by definition.

demand management policies. In this section, we employ Poisson regression methodology to investigate the effect of the characteristics of the commuter and of the commuting environment on the observed departure time, route, and joint switching behavior.

Background for Poisson Regression Models

The development of the Poisson regression model of the number of daily switches made by commuters is described in this subsection. Given the nature of the process and the inherent randomness in the number of switches made by different commuters, the Poisson distribution is likely to provide a reasonable description of the total number of switches made by a commuter during the study period. This distribution is particularly appropriate because the dependent variable naturally assumes nonnegative integer outcomes, including a relatively large number of commuters with zero switches (a problem that makes OLS regression biased).

One difficulty encountered here and in surveys of this type is that participants may have completed an unequal number of days for analysis (e.g., some participants completed the full 10 diary trips, but for various reasons others completed only 8 or 9). Standard Poisson regression applications assume an equal number of trials. For this work, the model was derived for different numbers of observed days per commuter. For Commuter i, let d_i denote the total number of days recorded, y_i the total number of switches made, $\lambda_i = E(y_i)$, and α_i the mean number of daily switches (i.e., $\alpha_i = \lambda_i/d_i$). The model postulates that the mean daily switching frequency (or rate) for Commuter i can be related systematically to the characteristics of the commuter. Assuming a specification of the form

$$\log \alpha_i = \beta \mathbf{X}_i$$

then

$$\log \lambda_i = \log \alpha_i d_i = \beta \mathbf{X}_i + \log d_i$$

where β is a vector of estimable parameters and $\mathbf{X}_i$ is a vector of commuting and socioeconomic attributes for Individual i. Note that the value of $\exp(\beta \mathbf{X}_i)$ represents the mean daily number of switches for Individual i. Therefore, the probability of a commuter making y_i switches in d_i days is given by

$$P(y_i) = [\exp(-\lambda_i)\lambda_i^{y_i}]/y_i!$$

The parameter vector β can be estimated by the maximum likelihood method. The log-likelihood function for the preceding specification (substituting for λ_i) is given by

$$\log L(\beta) = \sum_i [-\log y_i! - \exp(\beta \mathbf{X}_i + \log d_i) + y_i(\beta \mathbf{X}_i + \log d_i)]$$

The change from the initial log-likelihood value ($\beta = 0$) to the final log-likelihood value (at convergence) provides an informal measure of the model's goodness of fit. The log-likelihood value for a specification consisting of only a constant term (i.e., assuming that all individuals in the sample have the same mean daily switching frequency) is also provided for each of the models in this section. In each of the calibrated models, the constant term is expected to be negative to compensate for the addition of the log d_i term required for the estimation of a mean daily frequency.

The principal explanatory variables considered in the switching frequency models are given in Table 3. These include workplace, personal, commuting, and network variables. To show the effect of trip chaining, the stops ratio (number of trips with stops to total trips) was explored as a potential explanatory variable in the model specifications. Commuters with less than three trips or less than three switching opportunities were excluded from the following models, because (*a*) several essential explanatory variables could not be meaningfully calculated for these users (e.g., the stops ratio and travel time variability measures), and (*b*) the behavior of these individuals did not provide the multiday character that was intended by the specifications. Those left out of the models are a random subsample of the other commuters, since the factors that caused people to report fewer days were not correlated with the same characteristics that determine the modeled behavior (e.g., the individual was sick, on vacation, or on a business trip). Therefore, the exclusions did not create endogeneity in the model specifications.

Note that the developed models correspond to actual switching behavior and are not simply describing a propensity

TABLE 3 Independent Variables Tested in Evening Departure Time, Route, and Joint Switching Frequency Models

Independent Variable	Description/ Remarks
work end time	official work end time (median), not actual
type of work hours	regular, flexible, shift, and other
early preferred arrival time	preferred arrival time before the official work start
lateness tolerance at workplace	describes perceived ability to arrive at work after the official work start
stops ratio (PM)	ratio of number of PM trips with stops to total number of PM trips
routine stopper indicator (PM)	describes a commuter that makes a stop at the same location during at least 3 of 5 commutes
alternate route availability	indicator variable that describes the availability of meaningful route choices in the network
average travel time (PM)	travel time for days without stops only
standard deviation of travel time (PM)	for days without stops only
coefficient of variation of travel time	standard deviation divided by the mean tt
average speed	average travel speed for trips without stops
average travel time on mode route	travel time for days on which the mode route was taken (for route switching model)
average speed on mode route	average travel speed for days on which the mode route was taken
travel distance on mode route	network travel distance of mode route
radio traffic report listening indicator	describes whether or not commuter usually listens to radio traffic reports during commute
job power (as a function of job title)	indicator variable which represents the degree of schedule control, power, and responsibility associated with a particular job title
home ownership indicator	describes whether the participant's place of residence is bought or rented
gender	male/female
age	5 age group categories were available

to switch one's departure time or route, as in the models developed for the first-stage questionnaire of this research effort (*7,8*). General comparisons of the models developed here to describe actual behavior with those describing reported propensity to switch (with traffic conditions in mind) will be made where appropriate. Some disagreement between switching propensity and actual switching frequency is expected. This disagreement will be a result of definitional issues as well as the complex human behavioral considerations (including trip chaining) present in a real commuting system. Note that the models developed for the first-stage survey were calibrated for those with regular work hours only, whereas those developed here did not explicitly exclude other types of work hours.

Departure Time Switching Frequency

Because the alternative departure time definitions exhibit the same general trends, the model is presented only for the day-to-day switches that exceed a 10-min threshold, for days with the usual work end time. The work end time is controlled here so that the observed switching behavior is not a result of different work schedules. Thus, some commuters with shift work hours were excluded from the estimation data set.

Table 4 contains the attributes found to be important in the evening departure time switching frequency model (and the route and joint switching frequency models) and their corresponding parameter estimates and *t*-statistics. Workplace attributes, individual characteristics, and traffic system characteristics influence departure time switching behavior in the evening.

Lateness tolerance and travel time variability (expressed here as the coefficient of variation) increase the expected number of departure time switches of trip makers. It is interesting that lateness tolerance increases the likelihood of p.m. time switching, even though it is generally used to describe flexibility in the a.m. work start time. This may be a result of workplace rules (in terms of working a specified number of hours). It may also be capturing other job characteristics (such as job power or overall flexibility). The only other workplace variable included in the specification is a late work end time indicator, which can be interpreted as a traffic system characteristic. The negative coefficient indicates that those with work end times of 6:15 p.m. or later are expected to make fewer departure time switches than those whose work ends earlier. Therefore, those with late work end times are less willing to further delay their departure. Of course, there is no need for them to do so because the p.m. rush hour in Austin typically ends by 6:15 or 6:30.

The socioeconomic and individual attributes included in the model correlate negatively with departure time switching. Those making at least one routine stop during the evening trip are likely to make fewer switches, probably because they are constrained by their stop (which is likely to be a serve passenger stop). Males over 44 years of age also make fewer switches than others. This finding could be an indication that older males are inclined to be risk averse and creatures of habit and may have fewer household responsibilities that require deviating from an established routine. The home ownership indicator variable suggests that those renting make fewer evening time switches than those owning. Perhaps this variable is capturing a group of socioeconomic and life-style effects that determine risk aversion and habit persistence.

TABLE 4 Estimation Results for Poisson Regression Models of Daily Switching Frequency for P.M. Commute (Calibrated for Those with at Least Three Switching Opportunities)

	DEPARTURE TIME[a]		ROUTE[b]		JOINT[c]	
Independent Variable	Estimated Coefficient	t-statistic	Estimated Coefficient	t-statistic	Estimated Coefficient	t-statistic
constant	–0.730	–7.01	–2.018	–18.02	–2.283	–8.35
lateness tolerance at workplace (1 if over 5 min)	0.241	2.27			0.237	1.81
late work end time indicator[d] (1 if work end time ≥ 6:15)	–0.609	–2.23				
late PM peak hour indicator[d] (1 if work end is between 5:46 and 6:15)			0.534	2.26		
PM peak period work end time indicator[d] (1 if work end time is between 5:15 and 6:15)					0.268	1.35
PM routine stopper indicator (1 if makes a routine stop on PM commute)	–0.436	–2.84				
PM stops ratio, if less than 0.75 (0.75 if ratio ≥ 0.75)			2.190	8.41	1.724	6.08
additional PM stops ratio over 0.75 ([ratio–0.75], if ratio ≥ 0.75)			–2.295	–2.84	–4.159	–2.28
coefficient of variation of non-stop PM travel time (std. deviation travel time / mean travel time)	1.595	2.82			0.930	1.51
PM mode route medium length travel time indicator (1 if average tt is between 20 and 30 minutes)			0.222	2.01		
home ownership indicator (1 if renting, 0 otherwise)	–0.431	–2.54				
male over 44 indicator (1 if male and over age 44)	–0.150	–1.43				
age indicator (1 if age is between 30 and 60)					0.332	1.35
Log-likelihood at zero	–335.38		–700.76		–465.59	
Log-likelihood for constant only	–263.71		–346.38		–243.07	
Log-likelihood at convergence	–244.82		–289.33		–212.32	
Number of observations	121		160		121	

[a] 10-minute day-to-day definition, work end controlled
[b] mode route switching (all days definition)
[c] 10-minute day-to-day (WEC) departure time and day-to-day route definition
[d] Median PM departure time used for five individuals without official work end times (flexible hours).

Surprisingly, job power, an indicator variable intended to capture the degree of schedule control, power, and responsibility associated with a particular job title, was not found to significantly influence the p.m. departure time decision. It was thought that those with low-power jobs would make fewer switches than those with high-power jobs, but the hypothesis was not supported by the results. The effect of job type may have been confounded with other variables, such as age, gender, and housing tenure. Perhaps a finer grouping of job type would have been necessary to detect such significance. Flexible work hours also did not significantly influence the frequency of switches, though the effect may already be captured by other related variables.

Estimation results for the binary logit models of evening departure time and route-switching propensity from the first-stage survey are given in Table 5 (7). Comparison of our results with the first-stage binary model of p.m. departure time switching propensity reveals two similarities. First, males have a lower propensity for switching than females in both models. Also, two p.m. peak-hour indicator variables in the first-stage model indicate an increased switching propensity for those with work end times between 4:45 and 6:15 p.m. This is consistent with the finding here that users with late work end times switch less frequently than others. The other three varibles in the first stage model are reported travel time (positive effect), an alternate routes indicator (positive effect), and preferred arrival time for those without lateness tolerance (negative effect). These three variables were found to have no significant influence on actual departure time switching frequency for the p.m. commute.

Route Switching Frequency

The route switching modeled here is obtained with the mode route (all days) definition, which captures switches relative to a commuter's usual route (regardless of the magnitude of the switches). Table 4 contains the attributes included in the specification of the route-switching frequency model, along with their corresponding coefficient estimates and *t*-statistics. The p.m. stops ratio is the most important explanator of route-switching behavior. Two traffic system (or commute) attributes are included in the specification: a late peak-hour indicator and a medium length travel time indicator.

As expected, the route-switching frequency increases as the stops ratio increases, up to a point (0.75 in this model). Beyond this threshold, the likelihood of route switching actually decreases (as illustrated by the negative coefficient for the additional stops ratio), because routine stoppers (or others with a high stops ratio) may travel the same route on most trips. The late p.m. peak-hour indicator reveals that those having work end times between 5:46 and 6:15 make more route switches than other commuters. This is probably a reflection of the congestion experienced during this period, as commuters make more route switches in order to avoid delays. The last variable to display significance in the model is a mode route medium length travel time indicator, because those with travel times between 20 and 30 min switch more frequently than others. This variable may reflect the lack of opportunity in the network for significant improvements for very short or very long trips. It may also reflect a fundamental behavioral tendency: travelers with short trips may see no need for al-

TABLE 5 Estimation Results for Binary Logit Models of Departure Time and Route Switching Propensity for the Evening Commute from Work to Home[a]

PM SWITCHING PROPENSITY MODELS: (Stage 1 Sample) (values shown are the estimated coefficients)		
Independent Variable	DEPARTURE TIME	ROUTE
Constant	-1.396*	-1.227
Reported Travel Time in Minutes (tt) (0 if tt< 10, tt if ≥ 10)	0.025*	
Reported Travel Time in Minutes (tt) (0 if tt< 10, tt if 10 ≤ tt ≤ 35, 35 if tt > 35)		0.046*
Approximated Travel Speed in mph (spd)		-0.018
Lateness tolerance at the Work Place (1 if unlimited tolerance, 0 Otherwise)		0.343
Early PM Peak Hour Indicator (1 if work end time is between 4:45 and 5:45, 0 Otherwise)	0.282	
Late PM Peak Hour Indicator (1 if work end time is between 5:46 and 6:15, 0 Otherwise)	0.854*	
Preferred Arrival Time (pat) in minutes before work starts for commuters with no lateness tolerance at the Work Place (PAT if no lateness tolerance, 0 Otherwise)	-0.017*	
Abundance of Alternate Routes Indicator (1 if available, 0 Otherwise)	0.666*	0.744*
Age Group (1 if age<18, 2 if 18≤ age <30, 3 if 30≤age<45, 4 if 45≤ age ≤ 60, 5 if age >60)		-0.185
Radio Traffic Report Listening Indicator (1 if listens, 0 Otherwise)		1.311*
Gender (1 if male, 0 if female)	-0.557*	
Number of observations	393	365
Log-likelihood at zero	-272.40	-253.00
Log-likelihood at convergence	-221.70	-223.01

* Estimate has t-statistic of 1.85 or higher.
[a] Calibrated for commuters reporting regular work hours only.

Source: Caplice (1990), Tables 4.10 and 4.11.

tering routes (small absolute time savings), whereas those with long trips may face too much uncertainty with regard to travel time variability to distinguish one route's superiority over another. Surprisingly, the alternate route availability and travel time variability attributes did not show significance by themselves or in combination with other variables. However, the effect of these attributes may have been confounded with that of the late p.m. peak-hour indicator. No other attributes were found to significantly influence route-switching behavior for p.m. trips (including route speed).

Comparison with the binary logit model of evening route-switching propensity for the first-stage survey reveals no direct similarities (see Table 5). The most important variables in the first-stage model are travel time, availability of alternate routes, and the radio traffic report listening indicator, all exerting positive influence on route-switching propensity. These variables were not found to influence actual switching frequency. The only potential similarity in the model of actual switching frequency is to travel time, since the stops ratio is highly correlated with travel time (*9*). The other three variables in the first-stage model specification were approximate travel speed (negative effect), age (negative effect), and lateness tolerance at the workplace (positive effect). These three variables also had no significant influence on route-switching frequency for the evening commute.

Joint Route and Departure Time Switching Frequency

A joint switch is modeled here by a day-to-day route switch and a 10-min day-to-day departure time switch (with controlled work end times). Because the multinomial logit models developed for the joint departure time and route-switching propensity for the first stage contained no new variables other than those included in the individual models, no further comparisons are made between actual switching and reported propensity for joint switching.

Estimation results for the day-to-day joint switching frequency model for evening commutes are also given in Table 4. As expected, most of the explanatory variables in the joint model are derived from the two individual p.m. switching models. The stops ratio variable is specified as in the evening route-switching model, with similarly signed and equally significant variables. The lateness tolerance indicator and coefficient of variation of p.m. travel time (for trips without stops), significant in the evening departure time switching model, are moderately significant in the joint model.

The other transportation system and workplace attribute in the model is the p.m. peak period work end time indicator. Those with work end times between 5:15 and 6:15 are likely to make more joint switches than those with other work end times, although the coefficient is not strongly significant. This finding again stresses the importance of actual work end times, since those with these work end times find themselves returning home during the peak p.m. traffic period, which may provoke them to seek alternate routes and departure times. The two individual p.m. switching models also contain a work end time indicator variable, in slightly different forms, which are consistent with the joint switching behavior captured here. The last and only other new variable is a socioeconomic attribute: commuters between the ages of 30 and 60 tend to make more frequent joint switches than older or younger trip makers. This may reflect more complex activity and work patterns for middle-aged commuters, resulting in the need for more joint switching.

The models presented in this section provide helpful insight into the factors affecting commuter switching behavior and peak-period variability. The workplace, commuter, and transportation system variables exhibit plausible signs and significance in all three models. The significance of the stops ratio variable in the route and joint switching models emphasizes the need to understand trip-chaining behavior in a commuting context. A daily stop frequency model for the evening commute, based on the Poisson techniques described here, can be found in Hatcher (*9*).

CONCLUDING REMARKS

This study has provided insight into the trip-scheduling and route choice behavior of commuters for the trip from work to home. The presentation focused on the observed variability of the work trip, which has traditionally been treated as a stable and repetitive phenomenon. About 39 percent of all reported commutes contained at least one intermediate stop, underscoring the importance of trip linking in commuting behavior. Furthermore, trips with stops are much more likely to involve route or joint switching than trips without stops. Trip-scheduling flexibility for the evening commute appears to contribute to a substantial amount of departure time switching. In general, commuters tend to change departure times more frequently than routes, possibly a reflection of a limited route choice set in comparison with a broader set of available departure times.

Emphasis was placed on the definitional issues that arise when studying these behaviors. The analysis used both a "day-to-day" and a "deviation from normal" approach to switching behavior. The day-to-day definition captured a higher frequency of switching than did other definitions.

The models of daily switching frequency related the characteristics of the commuter, workplace, and transportation system to the switching behavior exhibited by the users. The stops ratio is an important determinant in all of the switching models except the evening departure time switching model (in which a routine stopper indicator is contained). Commuting trip time variability is an important determinant in all of the reported switching models except the evening route-switching model, where a medium length travel time indicator displayed significance without interacting with a variability indicator.

Workplace variables such as lateness tolerance and work end time otherwise dominate evening departure time, route, and joint switching behavior. Socioeconomic variables such as gender, age, home ownership, and interaction variables containing gender also display explanatory power, but their effect is not as clear-cut. The lack of agreement and strong significance for socioeconomic variables indicates that they may not be as important in the models as the other variables. Other personal and household characteristics may be important, but the limited availability of personal and socioeconomic exogenous variables precludes their inclusion in the model specifications. Furthermore, some of these characteristics may be indirectly reflected through their effect on trip-chaining patterns, as well as commuter preference indicators.

Although the data are somewhat limited, the behavioral insights gained from this study are important in that actual behavior was observed over a 2-week period rather than only 1 or 2 days. Furthermore, the documentation of actual switching habits is subject to fewer problems than a phone or mail survey, which involves recall or stated intentions by the respondent. Route and departure time switching were shown to be already taking place in actual systems, implying that users may be willing to shift commuting patterns if they were to benefit from these changes. In addition, this study has provided valuable confirmation of insights previously suggested in stated preference experiments involving actual commuters in a simulated traffic system. These findings contribute to the increasingly important task of understanding commuter behavior in real systems.

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Teleworking in the Netherlands: An Evaluation of Changes in Travel Behavior—Further Results

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The first two teleworking experiments in the Netherlands are described, and the results of an analysis of the impact of teleworking on the travel behavior of the participants and their household members during the experiments are presented. The mobility evaluation was designed as a multiple panel with waves at approximately 3-month intervals. The two experiments were analyzed and evaluated separately. Most important was the reduction of commuting trips (−15 percent) found in both experiments. The reduction is somewhat lower than expected on the basis of the percentage of time used for teleworking (18 to 24 percent) due to the freedom given in arranging teleworking time. The first experiment showed a considerable reduction of peak-hour automobile traffic (26 percent), which explains most of the commuting reduction; in the second experiment the reduction of commuting trips was due to fewer bicycle trips and public transport trips in the later waves. Car use was not influenced at all in the second experiment. A final important difference between the results was the lack of mobility effects for the household members in the second experiment. The first experiment indicated a surprising reduction of mobility not only for the teleworkers themselves but also for their household members. This result did not recur in the second experiment. Analysis of the dynamics of the process seems to indicate that a year may be too short a time span for monitoring such an experiment.

The Second Transport Structure Plan (*1*) aims to combat the problems related to an increasing mobility of persons and goods with a comprehensive set of measures. One of those measures is to stimulate teleworking—working at home using computer, modem, and fax. Teleworking involves less commuting and provides workers with the flexibility to make use of the available traffic infrastructure outside of peak hours. The aim formulated in the Structure Plan is to reduce automobile traffic by 5 percent in peak hours by making use of the possibilities provided by telecommunication. According to the Ministry of Transport, ". . . a substantial group of well-educated workers with relatively little leisure time will embrace the opportunities offered for making times and tasks flexible by teleworking, at home or in regional work centres. The expenses related to traffic jams and the rising travel costs will stimulate this development even more." Another conclusion is that ". . . an experiment conducted by the Ministry of Transport will bolster the further adoption of teleworking" (*1*). To evaluate the effects of teleworking, the ministry has set up two small-scale, in-house experiments intended to determine two types of effects.

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First, the operational effects of teleworking were carefully studied, because acceptance of teleworking will in large part depend on the effects it has on the quality and productivity of the completed work and company management aspects. Of course the evaluation of mobility effects is of primary importance in transport policy. The results of this evaluation are the subject of this report. The evaluation was commissioned by the Project Bureau for Integrated Transport Studies and carried out by Hague Consulting Group (*2,3*). The goal of the evaluation was to trace changes in

- The number of trips for both commuting and other reasons,
- Times of transportation (peak and off-peak hours),
- The days of travel (workday versus weekend), and
- The choice of mode (car, public transport, and bicycle).

The evaluation was directed at both the teleworkers and their household members with the aim of determining direct as well as possible indirect effects.

ORGANIZATION OF THE TELEWORKING EXPERIMENTS

For both teleworking experiments a total of 60 participants were recruited, all employees of the Ministry of Transport. The 30 participants in the first experiment were selected from three departments based in Amsterdam, The Hague, and Rotterdam. All participants in the second experiment were employed in the same department in Rijswijk, a small town bordering The Hague.

The selection of the employees was based on the following criteria:

- The employee's work is suitable for teleworking and colleagues and supervisor agree to the experiment;
- All levels within the organization are represented in the experiment;
- The employee is willing to work a minimum of 20 percent and a maximum of 60 percent at home, the time to be organized at the teleworker's discretion;
- The employee is committed to participating in all training sessions and evaluations connected with the experiment; and
- In the first experiment, commuting is done by car, preferably over long distances.

The selection was geared to maximizing mobility effects and simultaneously minimizing the experimental dropout. A consequence of this selection is that the results of these studies cannot be generalized to other populations.

All participants were provided with a PC, modem, fax, an extra telephone line, and special software. After a training session, the first experiment began on April 1, 1990, and the second on October 1, 1990.

EVALUATION OF MOBILITY EFFECTS

Method

To assess the effects of teleworking on the travel behavior of the participants, a panel was established in which the teleworkers and household members 18 years and older participated. Approximately every 3 months a mobility measurement (wave) was carried out. During the first experiment, five waves were collected (in March, June, September, and November 1990 and March 1991); in the second experiment one wave less (in September and November 1990 and March and June 1991). The setup, a multiwave panel, had a number of advantages over a simpler construction. First, the experimental group was very small. Repeated measurements from this group can be combined for analysis, thus mimicking a larger group. Second, analysis of the waves separately can provide insight into the dynamics of a change. Moreover, a panel setup is extremely suitable for measuring changes in a population that, in principle, remains unchanged.

No control group was established for this study. The expectation was that a control group, required to fill in a large number of forms without being "rewarded" with teleworking, would be substantially less motivated in participating in the evaluations and thus would obscure rather than clarify the results.

Survey Instrument

The mobility data were collected using a self-administered 7-day travel diary composed of two parts. The first part included personal questions, and the second consisted of a series of questions per trip. The personal questions dealt with age, gender, possession of driver's license, and ownership of means of transportation. The trip-related questions included date, origin, origin activity, time of departure, destination, destination activity, time of arrival, transportation mode (chain of up to seven modes), estimated total distance, and, if a car was used, the occupancy.

Survey Procedure

Both groups of 30 households were divided into six groups of approximately 5 households. Each group would begin a wave on a predetermined day of the week (Monday through Saturday). Thus, the procedure was carried out according to a staggered method to ensure that each weekday was equally well represented in the data. The participants were asked to record each trip during the following 7 days in the travel diary, so that each wave lasted a total of 2 weeks.

To maximize the response for all waves, the participants were provided with a great deal of information and received a personal letter before each wave. In addition, on the evening before their designated starting date, each household was contacted by telephone. This contact was mainly a reminder of the correct starting date and in later waves was used to correct ambiguities in previous diaries, but participants could also ask questions, and household members could be given extra motivation. The travel diaries were returned in prestamped addressed envelopes. Reminders were carried out by telephone 14 days after each wave.

Data Entry and Analysis

Upon receipt, each travel diary was checked, and in the case of unclear data the respondent was consulted. The data were entered chronologically for each travel diary with the use of a program containing checks for inconsistencies. A number of derived variables were added. Next, the mobility data were aggregated for each respondent according to number of trips and the total kilometers traveled, broken down by the following criteria:

- Time of day (peak versus off-peak),
- Type of day (workday versus weekend),
- Purpose (commuting, business related, and other reasons), and
- Main means of transport [public transport, car (driver), car (passenger), bicycle, and other].

For each wave a separate data set was constructed with 15 trip categories, not all mutually exclusive. Considering the modest scope of the experiment, a further segmentation was not possible. The data from subsequent waves were then matched for each person to the mobility data from the first wave. In this matching of wave pairs, only those households were included that had experienced no unusual circumstances during either wave (usable diaries). This means that only mobility patterns were compared for those respondents who had participated in the first wave and had not moved, changed work, been ill, had a baby, and so forth in the later wave. If one household member had been ill, the whole household was deleted from the analysis on the assumption that the other members might change their mobility pattern to compensate.

For the analysis of the pattern of mobility effects, each wave pair comparison was tested separately for each segment for changes in frequency and distance traveled. To determine the average mobility effects, the wave pair comparisons were combined and analyzed for each segment using a series of pairwise *t*-tests. Pairwise *t*-tests were used because they are extremely efficient in testing for differences between two related samples and make it possible to assess not only the direction of differences but also their size and confidence interval. However, the distribution of trip frequency is not normal and strictly speaking would require a nonparametric testing method. Therefore, in addition to a series of pairwise *t*-tests, an analogous series of Wilcoxon signed ranks tests was carried out. The results of both analyses were nearly identical and for the rest of the study the pairwise *t*-test was retained.

Response and Mobility

The first experiment was launched on April 1, 1990, and the second experiment began 6 months later on October 1, 1990. Each experiment was preceded by the first wave, which served as the basis for an evaluation of the changes. For practical reasons the waves for the two experiments ran parallel as much as possible. Table 1 gives the response, which is unusually high (almost 100 percent).

More than half of all households consisted of families with one or more children (58 percent), and 12 percent of all teleworkers lived alone. The first group included fewer families and more single persons than the second group. Only two households (3 percent) did not own a car, more than 70 percent of the households had one car, and one household (1.5 percent) had three cars.

In both experiments the experimental group was 5 to 8 percent more mobile than the average person in the Netherlands (*4*). Compared with the national statistics, the panel members of the first group traveled more than double the distance an average person in the Netherlands travels in a day. The second group also covered 60 percent more kilometers. The commuting distance in particular was greater (3 to 4 times), and the greatest distance was covered by car drivers (1.5 to 2.5 times). The differences were primarily caused by teleworkers and are a logical consequence of the selection criteria.

ANALYSIS OF MOBILITY EFFECTS

In this section the results of the two experiments will be discussed. For the first analysis, all the wave pair data are pooled per experiment. The pooled sample becomes larger and, by extension, the statistical precision of the tests becomes greater. Underlying this procedure is the assumption that all respondents are independent—in reality this is not the case—resulting in an overestimation of the *t*-values. The results of this first pooled analysis prompted a short evaluative survey, which is also treated.

The third analysis is based on a series of single wave pair comparisons. In a number of graphs the dynamics of the change process are visualized. Because of the changing comparison group per wave, all changes in trip frequency are calculated relative to an indexed base trip frequency (100 percent). The statistical results of this analysis are available on request (*1,2*). For each wave comparison the group is small, and therefore the precision of the statistics is lower, but because all respondents are, in fact, independent, the *t*-values are correct.

Average Mobility Effects

Table 2 gives the result of the analysis of the pooled wave pairs. In both experiments the mobility of teleworkers decreased the most. The number of commuting trips decreased by 15 percent. In contrast to the first experiment, in which the use of the car decreased sharply, the reduction in commuting trips in the second experiment is explained for 83 percent by less public transport and bicycle trips, whereas travel by car was not reduced at all.

In both experiments the reduction is distributed equally over movements in peak and off-peak periods. Travel during the weekend, which revealed a marked decline in the first experiment, did not change in the second experiment under the influence of teleworking. Moreover, in the second experiment longer trips were made during the weekends.

The first experiment indicated a significant reduction in the mobility of household members. This result is totally absent in the second experiment.

Short Evaluative Survey

In the first teleworking experiment the commuting mobility of the teleworkers was reduced significantly and all other purposes showed a lower mobility. Also the household members displayed a lower mobility. In an effort to explain this finding, a short evaluative survey was carried out. In this survey all respondents were asked to describe their experiences with teleworking (their own or that of their household member). Teleworkers and their family members were all very positive in their evaluation. All hoped for a continuation of the experiment. The teleworkers had not perceived any change in their own mobility besides the elimination of certain commuting trips; neither had they noticed a change in the mobility of the family due to their teleworking. The household members were of a similar opinion. The panel members had not used teleworking for streamlining activities or major rearrangement of tasks.

Pattern of Mobility Effects

On the basis of the single pre-and postcomparisons, graphs were produced providing insight into the pattern of change.

TABLE 1 Response to Mobility Evaluation Study of Two Telework Experiments

Month 1990-1991	First Teleworking Experiment			Second Teleworking Experiment		
	Wave	Response	Usable diaries	Wave	Response	Usable diaries
March	1	60 (100%)				
June	2	62 (100%)	47 (76%)			
September	3	58 (100%)	45 (78%)	1	62 (95%)	
November	4	58 (100%)	48 (83%)	2	63 (97%)	47 (72%)
March	5	56 (97%)	48 (83%)	3	58 (91%)	42 (74%)
June				4	60 (95%)	44 (70%)

TABLE 2 Results of Average Effects Analysis of Telework Experiments

	First Teleworking Experiment (n=188)				Second Teleworking Experiment (n=133)			
	trips[a]		distance[a]		trips		distance	
Segment	Tw[b]	Hm[b]	Tw	Hm	Tw	Hm	Tw	Hm
Total	-17%	-9%	-16%	--[c]	-10%	--	-14%	--
Peak	-19%	--	-26%	--	-11%	--	-22%	--
Off-Peak	-15%	-12%	--	--	-10%	--	--	--
Weekday	-18%	--	-18%	--	-13%	--	-25%	--
Weekend	-13%	-18%	--	--	--	--	+73%	+137%
Commuting	-15%	--	--	--	-15%	--	-16%	--
Business	-33%	--	-49%	+27%	--	--	--	--
Other	-14%	-13%	--	--	-15%	--	--	+46%
Public Transport	-18%	--	--	--	-63%[c]	--	-55%[c]	--
Car (driver)	-19%	--	-19%	--	--	--	--	--
Car (pass.)	-27%	-19%	--	--	--	--	--	--
Bicycle	-31%[c]	--	--	+35%[c]	-35%	--	-40%	--
Other	--	--	+55%[c]	--	--	--	+75%	--
Car/Peak	-26%	--	-34%	--	--	--	--	+34%
Car/ Off Peak	-17%	--	--	--	--	--	--	--

[a] Trips and Distance refer to trip frequency and total distance travelled per segment.
[b] Tw and Hm refer to Teleworkers and Household members.
[c] In absolute terms the change is small.
-- Change is not significant on a 10% level.

The graphs have been corrected for seasonal influences on the basis of the averaged monthly mobility over 5 years (1986 to 1990).

Figure 1 shows the observed total number of trips made by teleworkers and household members per wave pair for both experiments. The difference between the mobility of the teleworkers is immediately apparent. The mobility change in the first experiment is larger than in the second experiment. Even more obvious is the difference in behavior of the household members. In the first experiment the household members display a lower mobility, whereas in the second experiment the mobility of household members only starts to decrease in

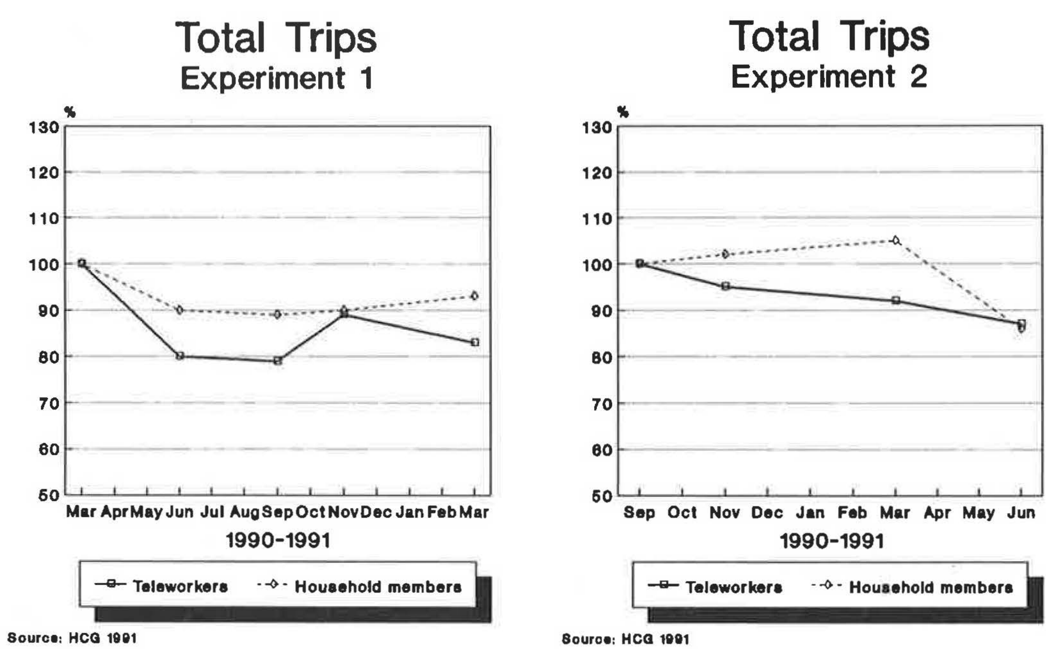

FIGURE 1 Change in the total number of trips for teleworkers and household members.

the last wave. The latter may indicate that 1 year is too short a period to monitor for secondary effects.

In comparing mobility by purpose (Figures 2 and 3), it becomes clear that in the second experiment the reduction in commute trips is fairly constant with a slight rise in the last wave. In the first experiment the dynamics were slightly different. Initially the teleworkers enthusiastically started working at home as much as they could; however, for a variety of reasons they returned to working in the office more (5). The decline leveled off at −10 percent in the later waves. In both experiments the mobility of household members is characterized by much larger spreads expressed in clearly larger confidence intervals and an erratic pattern. The seemingly large increase in commuting trips made by household members in June 1991 is not a result of increased employment, but rather a result of a low number of observations for this purpose.

In Figures 4 and 5, the difference in the results between both experiments is clear. Figure 4 shows the changes in mode for the first experiment. Here the decline of car use is very

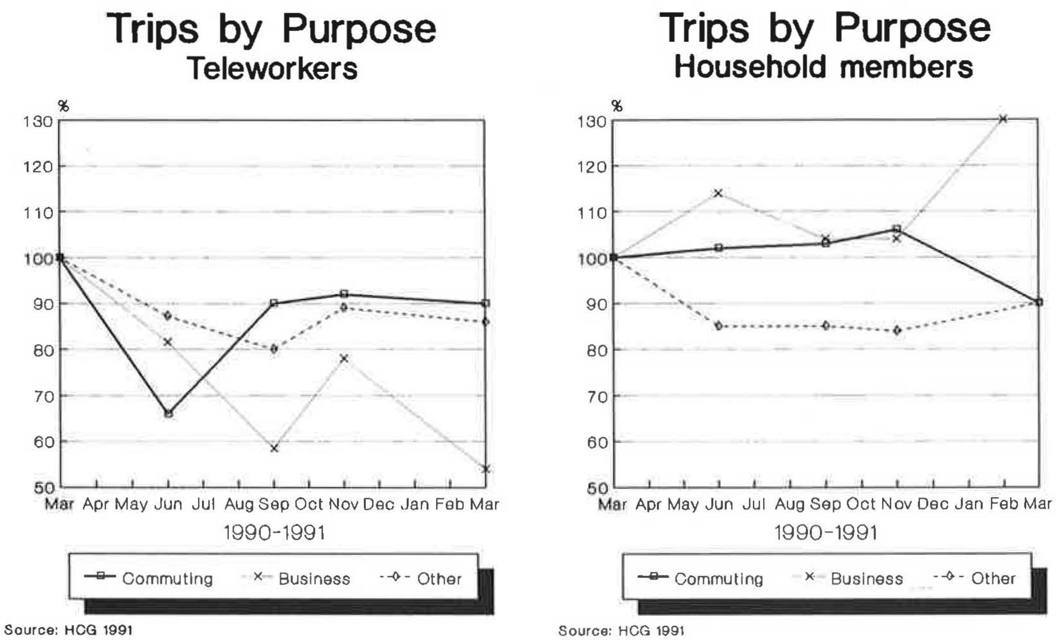

FIGURE 2 Changes in the number of trips by purpose (Teleworking 1).

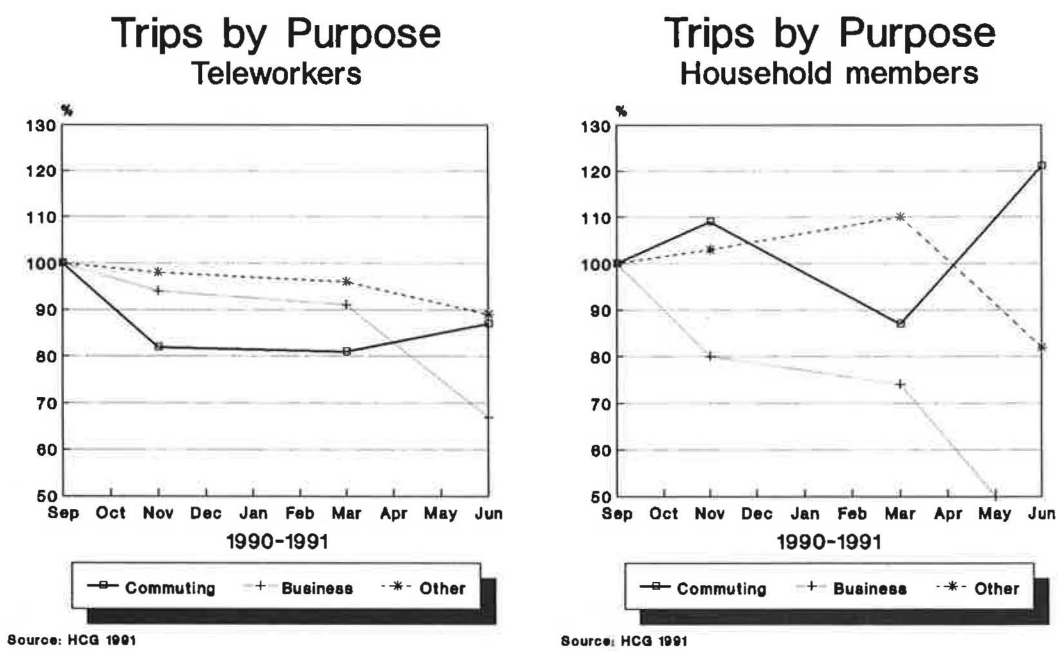

FIGURE 3 Changes in the number of trips by purpose (Teleworking 2).

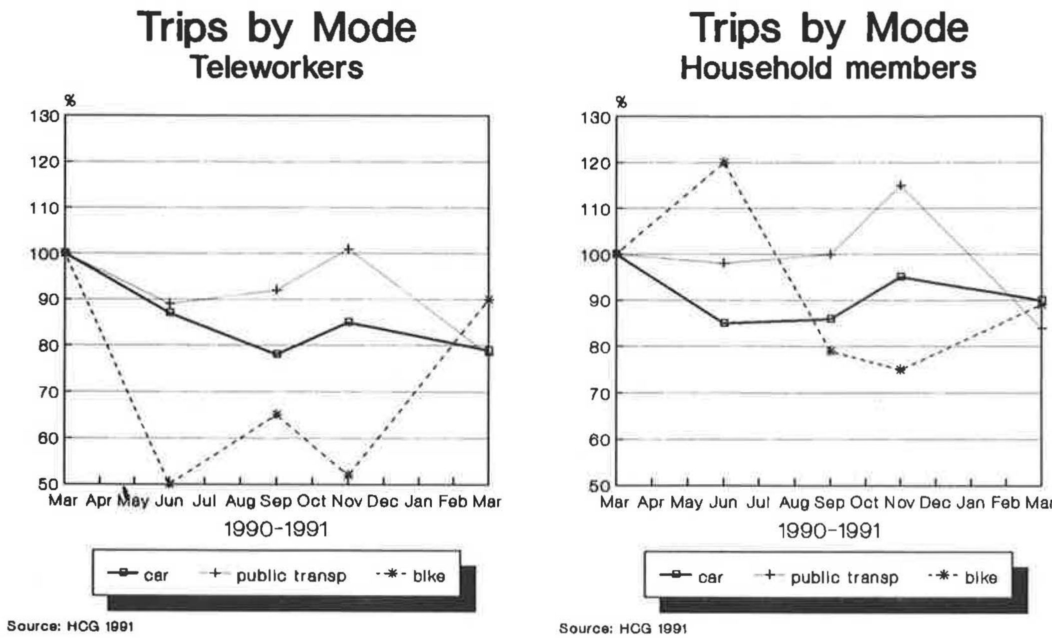

FIGURE 4 Change in the number of trips according to means of transportation (Teleworking 1).

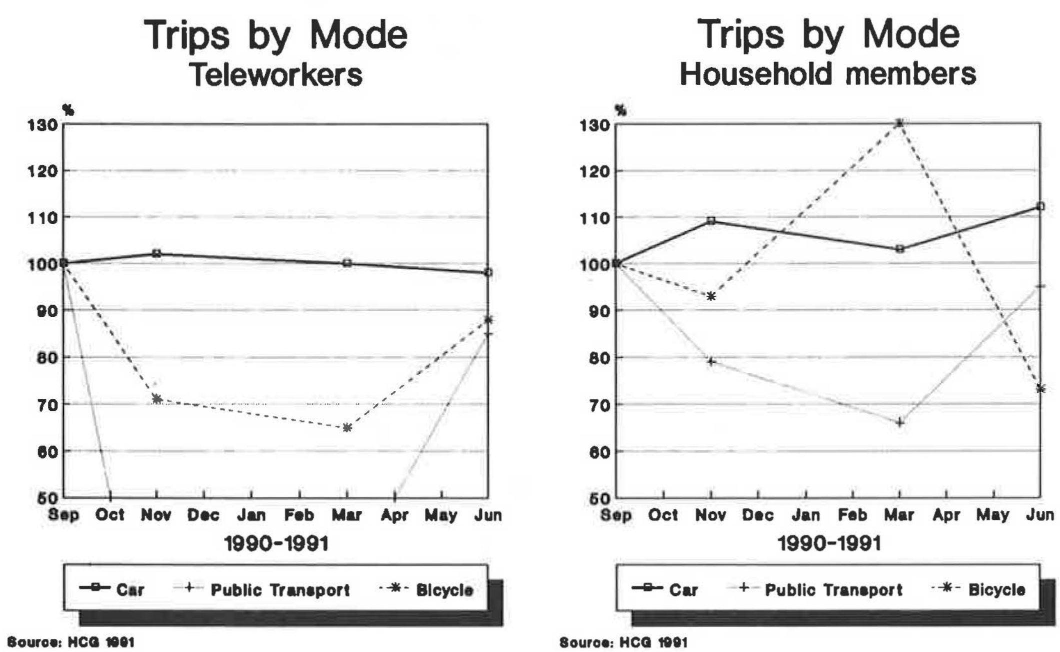

FIGURE 5 Change in the number of trips according to means of transportation (Teleworking 2).

obvious. By the second wave it had diminished by approximately 20 percent for the teleworkers and approximately 10 percent for the household members. In Figure 5, which shows the same changes for the second experiment, one can see that the teleworker's car use remains almost constant at the original level. The reduced mobility of the teleworkers in this experiment is explained almost totally by the elimination of public transport and bicycle trips. The mode pattern for the household members displays an even more erratic pattern after seasonal correction than before. The large increase in bicycle trips in March and the almost equally large reduction in June are apparent. This pattern emerged more clearly after seasonal correction and is due to an unusually warm March, leading to more trips by bicycle, and subsequently the coldest and wettest June in more than a century, leading to more transit use.

ANNOTATIONS

These results, encouraging as they may appear, call for careful evaluation. They may be in part the result of the experiment.

Because of the rigorous selection, especially in the case of the first experiment, these experiments are more likely to indicate a maximum result than an average one. This bias may be compounded, in the case of the first experiment, by an awareness of the importance of a reduction of mobility for the continuation of the experiment.

Part of the results may be explained by the measurement method. To check the influence of the so-called panel effects, a number of checks of the diaries were undertaken. We found no evidence that the observed reduction of mobility is due to trip underreporting in later measurements. There was no significant increase in average number of mistakes per trip, tripless days, or missing (return) trips indicating panel fatigue over the measurements. The reported mobility was almost level over all measurement days in all but one measurement. This feature may indicate almost no panel fatigue within each measurement and may also support the assumption of high motivation on the respondents' part to participate fully in all evaluations, adding credibility to the results. In the base measurement of the first teleworking experiment, a slightly higher mobility was reported on only the first measurement day. This deviation explains in part the household members' observed reduced mobility in the first experiment, while only slightly reducing the mobility effects for the teleworkers in the first experiment without changing the results of the analysis significantly.

We also tested whether trip chaining explained part of the observed mobility effect. Perhaps respondents had streamlined their activities and merely rearranged their trips, substituting simple home-activity-home chains with longer and more complicated ones. In that case part of the mobility effects may be due to elimination of trips. However, household members did not increase their trip chain length. Teleworkers even reduced the average chain length by 12 percent. This means that trip chaining did not add to the mobility effects of teleworking. Furthermore, during the experiments, no large-scale changes in policy were recorded that could account for a part of the mobility change. In fact the average (car) mobility in the Netherlands is still rising.

And finally, we analyzed whether within the group of teleworkers there were other characteristics that could give more insight into the mobility effects of teleworking. This analysis clearly indicated that commuting distance is important in ascertaining the effects of teleworking. Car use, especially during peak hours, is maximally reduced (20 to 40 percent) for commuting distances of 20 km or more. Shorter commuting distances lead to only slightly fewer commuting trips, and even then usually the bicycle trips are eliminated. Travel time, by the nature of things correlated with the distance, shows an even more clear pattern. Commuting times of 20 to 60 min show a clear reduction of commuting trips (20 to 30 percent), whereas even longer commute times also show a reduction in the low number of business-related trips.

DISCUSSION OF RESULTS

In a number of previous European studies, expected effects of telematics on mobility have been brought forward. Most expectations can be summarized with the phrase "some substitution of commuting traffic, but generation of mobility for other purposes and [most important] increased use of the now available household car" (*6–8*). These studies are for the rest mostly concerned with estimating the number of jobs suitable for teleworking. The results of both experiments treated here indicate that teleworking can indeed contribute to a reduction of the number of commuting trips. Furthermore, it contributes to distributing the use of the infrastructure, which is particularly scarce during peak hours. Finally, we found no indication of increased car use by household members.

A second comparison can be made with other evaluation studies. At this time only one similar experiment in California is known to us (*9*). The results of both Dutch and the California experiments are very similar. In California, teleworking reduces the number of commuting trips, and no new trips are generated. Also a marked reduction in trip frequency for nonwork purposes is found. However, in the California case there are some indications that the reduced mobility of the household members is partly due to trip underreporting (*10*). In the Dutch experiments there is no indication of trip underreporting. An extra survey, specifically undertaken to find an explanation for the reduced mobility of the household members, gave no insight into this phenomenon. However, during the selection of the participants for the first experiment, special attention was given to the importance of reducing car mobility. Perhaps this emphasis resulted in an increased awareness and subsequent reluctance to use the household car.

The experiments clearly indicate that teleworking can contribute significantly to reducing commuting traffic, yielding an average of 15 percent fewer commuting trips from 20 percent restriction-free teleworking time. However, in situations where there are competing modes, as in the Netherlands, the benefit of teleworking in reducing car traffic is less straightforward. The possibility of working at home will especially affect workers with relatively large resistances in their commuting trips. In the first experiment most participants traveled to work on the highways. They probably encountered resistance regularly in the form of peak-hour congestion. In the second experiment most commute trips were also made by car, but usually the highways could be avoided. It is very possible that this group of teleworkers met relatively little peak-hour congestion. On the other hand the work location in Rijswijk is difficult to reach by public transport. The results clearly indicate that precisely these public transport trips were almost entirely eliminated. Furthermore, traveling by bicycle has a higher resistance, and such trips also tended to be canceled in favor of more comfortable trips by car. This means that work location, its facilities, and commuting travel time, including time lost in congestion, are important aspects determining the benefits of teleworking for the reduction of car mobility.

Possibly, the effects of teleworking in particular reducing car traffic will increase with larger commuting resistances (i.e., longer distances or travel times). Commuters who have a large commute mobility may be traveling above their preferred mobility budget, and therefore when commute trips are eliminated there is little chance of generating more trips for other purposes. Under these circumstances maximum effects are to be expected. The impression is that the selection of the participants, in particular the first Dutch experiment, led to including almost exclusively commuters who operate above their travel budget. The mobility changes found in these experiments are more probably maximum than average effects.

Finally, a warning is appropriate: introducing more flexible work hours and work locations, for instance through teleworking, may result in workers accepting even longer commute distances for the remaining commutes. This long-term change might eventually even cancel out the initial positive traffic and environmental effects. In this sense the possibilities created by teleworking are comparable with those created by mass motorization. These long-term effects are not evaluated in this study.

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