comparison of transfer results to results obtained by application of a local model. The objective for the future is to use an understanding of the relation between model specification and characteristics of both estimation and application contexts to provide prior guidance about the probable transferability of different models estimated in different contexts for use in the application context of interest. This will be the focus of future research.

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Wisconsin Work Mode-Choice Models Based on Functional Measurement and Disaggregate Behavioral Data

GEORGE KOCUR, WILLIAM HYMAN, AND BRUCE AUNET

This paper describes a series of mode-choice models developed by the Wisconsin Department of Transportation to assess transportation policy issues consistently across four sets of urban areas in the state. The models were developed by using a combination of functional measurement (or by asking respondents their likely mode choice in a series of situations) and disaggregate demand modeling (to calibrate the models and provide a test of the correspondence between stated and actual behavior). Bus, walk, bicycle, ridesharing, and drive-alone modes are included. Key variables include gasoline availability, gasoline price, queuing time to purchase gasoline, bicycle lanes, ridesharing programs, and transit service improvements. The models are being used in statewide policy analysis, for local planning, and for quick-response analysis. They represent an approach to demand analysis and may be an efficient and effective tool for examining other demand issues.

In a single statewide modeling study, the Wisconsin Department of Transportation (WisDOT) has developed work trip mode-choice models for four sets of urban areas of different character: one large city, one medium city, and two sets of small cities. These models permit WisDOT to address key policy issues by incorporating the effects of gasoline availability, gasoline price, queues for gasoline purchases, ridesharing programs, transit service improvements, bicycle lanes, and other factors. The models are estimated by a combination of functional measurement (also called conjoint analysis) and disaggregate demand modeling. Functional measurement models (1,2) are based on asking respondents their likely mode choice in a series of situations constructed from an experimental design. One or more situations closely resemble current conditions. We use a logit model to compare stated behavior under current conditions with actual behavior and adjust the models derived from the functional measurement task if there is a difference. The models are further refined by using sensitivity analysis.

The department undertook this statewide effort to enhance its ability to plan in a multimodal context. By administering similar surveys in all the urban areas of the state, it gained the ability to examine a broad range of urban transportation policies in a consistent manner. The department can now determine the absolute and comparative impacts of many policy proposals on driving alone, sharing a ride, walking, bicycling, and riding a bus.

Not only are the models useful for statewide policy analysis, they also enhance WisDOT's ability to provide technical assistance to urban areas in preparing transportation plans. Also, the pivot point and elasticity formulations of these models are being used for quick policy analysis. Finally, these urban work trip models complement a set of intercity mode and trip-frequency models developed earlier by using functional measurement (3,4). Ultimately, the department will have a comprehensive set of models for statewide policy analysis and system planning.

The functional measurement and disaggregate modeling methodology was devised to address WisDOT's forecasting requirements within a moderate budget level and relatively short time frame. Functional measurement was chosen because most key policy issues that face WisDOT cannot be captured readily in disaggregate models. Top administrators were specifically interested in learning the effects of gasoline rationing, long lines at gasoline stations, large increases in gasoline price and parking costs, improved bicycle facilities, and other issues not customarily addressed by demand models. Fuel price and availability exhibit no variability in the usual cross-sectional data sets because all individuals face the same conditions at a given point in time. In small cities bus fares are constant and virtually no parking fees are charged for work trips. Several modes of interest, such as bicycle facilities and commuter rail, are nonexistent in most areas. Finally, the data-collection effort for a statewide disaggregate model would be extensive.

Model validity was a strong concern, so we performed a second stage of analysis by using a logit model to further calibrate the original models. In this stage the forecasts derived from the functional measurement model for the status quo are compared with actual behavior, and the stated behavioral model is adjusted if there is a discrepancy. The calibration procedure can require fewer data than a traditional disaggregate model.

Two staff members completed the analysis in six months. An additional six months was needed to prepare reports and documentation, and some programming, keypunching, and consultant assistance were required.

FOCUS GROUPS

To begin the analysis four focus group interviews were held. The discussions of the focus group either verified the factors believed to be important a priori or suggested others to be treated in the qualitative analysis of mode split. The focus group consisted of 8-12 individuals who were convened for 1.5 h in a structured session. We obtained several interesting qualitative results. For example, individuals said their travel behavior was more sensitive to the change in the pump price of gasoline than to gasoline price per mile, which suggests that fuel efficiency was a consideration only when buying a vehicle. Also, participants of the focus group regarding bicycle travel said condition of the riding surface was a major concern, which was an unanticipated factor. In addition, many women said that under no circumstances would they stop driving alone to work because they had to carry groceries or children on the way to or from work. This suggested that sex and the number of children should be included in the final models to explain travel choice (5).

DESIGN OF EXPERIMENTS AND SURVEY

Six experiments were prepared to meet the objectives of the study. The four that pertain to ridesharing, walking, bicycling, and local bus service are reported in this paper. Two other experiments for express bus and commuter rail were also administered, but these modes are available to few travelers in Wisconsin. The experiment for ridesharing is illustrated in Figure 1, and other experiments are very similar. All surveys used drive-alone as the base mode.

A typical multivariable experimental model involves a series of independent variables that affect some dependent variable, such as mode choice. Each independent variable is considered at two or more values or levels, as designated by the experimental plan. In the ridesharing experiment gasoline price has four levels ($1.30, $1.70, $2.00, and $2.60), and the four other factors have two levels. The experiment is thus a $4^1 \times 2^4$ design.

The experimental results are analyzed to evaluate the statistical significance of the independent variables, estimate their effects, and establish functional relations. In conducting such analyses, one is interested in the main effect of each variable, that is, the effect on experimental response of going from one level of the variable to the next, all other variables being at their average values. In many situations the effect of two independent variables is not additive, and the variables are said to interact (i.e., the effect of one variable on the response depends on the value of some other variable).

A common multivariable experimental plan is the full factorial experiment, which consists of all possible combinations of levels for each of the variables. In our case, this would require $4^1 \times 2^4$, or 64 situations. A full factorial experiment permits one to obtain estimates of the effects of all possible interactions.

Many higher-order interactions can be assumed to be negligible, which leads, however, to a substantial reduction in the number of situations required. Such designs are called fractional factorial plans. In Figure 1 we use a one-eighth fraction, or only eight situations; this assumes that all interactions are negligible. This plan allows approximate estimates of the effects of a large set of policy variables in a relatively simple mailout survey, although it is at the expense of assuming a linear, additive model without interactions. This trade-off between survey complexity and model richness was made to ensure as high a response rate to the survey as possible, and to allow high

Figure 1. Ridesharing experiment.

Under what situations would you drive alone or share a ride (carpool or vanpool) to work?

Consider that you are going to work and that driving alone or sharing a ride in a car pool or van pool are your only choices.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or share a ride to work.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or share a ride to work.

	AUTO FACTORS			CAR POOL/VAN POOL FACTORS		PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE ALONE OR SHARE A RIDE? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Parking Cost to Drive Alone	People You Share A Ride With	Employee Work Schedule	Always Drive Alone	Probably Drive Alone	In-different	Probably Share A Ride	Always Share A Ride
SITUATION 1	Ample Supply	$1.30/gallon	Free	Co-Worker/ Neighbor	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	Free	General Public (Carpool Matching)	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 3	Ration of 10 gallons/week*	$2.00/gallon	$30/month	Co-Worker/ Neighbor	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	$30/month	Co-Worker/ Neighbor	Fixed 8 hour day	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.70/gallon	Free	Co-Worker/ Neighbor	Fixed 8 hour day	1	2	3	4	5
SITUATION 6	Ample Supply	$2.00/gallon	Free	General Public (Carpool Matching)	Fixed 8 hour day	1	2	3	4	5
SITUATION 7	Ample Supply	$1.70/gallon	$30/month	General Public (Carpool Matching)	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 8	Ration of 10 gallons/week*	$1.30/gallon	$30/month	General Public (Carpool Matching)	Fixed 8 hour day	1	2	3	4	5

*If your car gets 15 miles per gallon, you can travel 150 miles per week.

confidence in the responses received--both crucial considerations for statewide policy planning.

Catalogs of experimental designs are available in the literature (6,7). We developed our own simple designs. In addition to the experiment, each survey instrument contained background questions of two types. Some were questions concerning socioeconomic characteristics of respondents and thus were suitable for checking representativeness of the samples and measuring the sensitivity of mode choice to socioeconomic variables. The remainder gathered data on actual travel choices of individuals and the attributes of competing modes.

SURVEY ADMINISTRATION

The sizes of the survey sample were determined based on desired levels of sampling error and expected response rates. The sampling error was set at ±5 percent, with 95 percent confidence for categorical variables, particularly the 1-5 response scale in the experiments. A conservative 20 percent usable response rate was assumed. These considerations, applied to the number of cities and separate modes for which models were desired, resulted in the mailing of about 17 000 questionnaires.

WisDOT mailed the surveys to residents who renewed their drivers' licenses in August and September 1980. The gross response rate was 57 percent (9208 surveys), but some surveys had incomplete information. The usable response rate was 46 percent. Because we received more than double the expected response rate, we were able to exclude respondents who did not travel to work, so we could compare each person's stated responses with actual travel choices. Respondents sorted out at this stage were retired people, other individuals who do not work, individuals who work at home, and students. Also, some respondents who filled out the walk or bicycle experiments were dropped because they lived too far from work to consider walking (more than 3 miles) or bicycling (more than 7 miles) as practical choices. We retained 3185 surveys for model development; 1791 of them pertain to the four models reported in this paper. Between 273 and 679 surveys were used in the four sets of urban areas.

We checked the samples for representativeness by comparing the frequency distribution of selected socioeconomic characteristics of respondents with 1970 census data. The proportions of individuals in any one-way tabulation by sex, age, household size, and income (adjusted for inflation) were within ±10 percent of the census. The only exceptions were that, in some cities, the 15-24 age category, one-person households, and incomes under $5000 annually were underrepresented. Exclusion of students, retired, and other unemployed respondents explains the difference.

As a further check of representativeness, we compared the actual mode choices reported by respondents with the results of a strict probability sample conducted a year earlier by the Wisconsin Survey Research Laboratory (8). The comparison was satisfactory.

ANALYSIS OF SURVEY RESPONSES

The first stage in building the actual models was to fit linear additive models on the experimental responses obtained in the survey. The functional form and variables were already set in the design step so that model estimation is a simple task at this stage. The only flexibility in model estimation is in the socioeconomic variables and their functional form because they are not part of the experimental design. Multiple linear regression is used to estimate the models. The dependent variable is the response on the 1-5 scale, assuming that the stated likelihood of choosing a nonautomobile mode is proportional to utility. This is equivalent to using a linear approximation to a logit function. The independent variables are the experimental variables (level of service) and the background responses (socioeconomic characteristics).

The automobile-related variables appear in each survey form because automobile was the base mode against which each competing mode is set. Restrictions that the coefficients of the automobile variables be equal across all experiments are required for consistency in the multimodal model developed in the next step; the easiest way to apply these restrictions is to estimate a multiple linear regression across all the surveys jointly. The results of this are given in Table 1.

Formally, the equations in the table are as follows:

$$U_{ai} = -\sum_k c_{ak}X_{ak} + \sum_l c_{sl}X_{sl} + \sum_m c_{wm}X_{wm} + \sum_n c_{bn}X_{bn} + \sum_p c_{tp}X_{tp}$$
$$= -U_a + U_s + U_w + U_b + U_t \quad (1)$$

where

U_{ai} = utility of mode relative to driving alone (i.e., the response to a situation on the 1-5 scale from any experiment i); i = s (shared ride), w (walk), b (bicycle), or t (transit);
c = vector of coefficients;
X = vector of variables in experiment s, w, b, or t; variables for mode a appear in all experiments;
k = index that corresponds to drive-alone and socioeconomic variables;
l = index that corresponds to shared-ride variables;
m = index that corresponds to walk variables;
n = index that corresponds to bicycle variables; and
p = index that corresponds to local bus transit variables.

The utilities U_a, U_s, U_w, U_b, and U_t are the absolute utilities of each mode (not relative to drive alone), which are used in the calibration step. The Xs are dummy variables; for example, all X_{1s} = 0 except when i = s. Thus, Equation 1 encompasses each binary experiment but allows a multimodal treatment by incorporating the restriction that the automobile utility coefficients are the same in all binary comparisons.

Table 1 gives the results of analyzing the experimental responses for each city. Most of the coefficients show relatively little variation across cities, which suggests that transferability of these coefficients among urban areas is a possibility.

Table 1. Variables, coefficients, and goodness-of-fit statistics for regressions on experimental responses.

Variable Name	Definition	Madison (n = 305) Coefficient	t-Value	Milwaukee County (n = 273) Coefficient	t-Value	Fox River Valley Cities (n = 534) Coefficient	t-Value	Other Cities (n = 679) Coefficient	t-Value
Automobile Utility (U_a)									
CA	Automobile constant	-5.271		-4.697		-4.448		-5.051	
GA	Gasoline availability, 0 if ample supply, 1 if rationing	-0.320	-6.30	-0.377	-6.57	-0.318	-7.93	-0.315	-8.99
GP	Gasoline price ($/gal)	-0.234	-5.48	-0.320	-6.62	-0.284	-8.41	-0.284	-9.59
PK	Parking costs ($/month)	-0.016	-6.93	-0.017	-6.91	-0.017	-8.77	-0.016	-9.82
WT	Wait time to buy gasoline (min)	-0.008	-0.89	-0.004	-0.38	-0.013	-2.30	-0.007	-1.29
IN	Annual household income ($000s in 1980)	+0.012	6.02	+0.010	3.73	+0.001	0.59	+0.008	5.09
VP	Vehicles per person 16 years old and over in household	+0.178	3.12	+0.078	1.19	+0.096	2.48	+0.004	0.13
TT	Travel time (min)	-0.030	-2.77	-0.025	-2.27	-0.019	-1.89	-0.33	-3.70
Shared-Ride Utility (U_s)									
CR	Shared-ride constant	0.216	3.08	-0.090	-1.21	0.360	5.91	0.085	1.61
RD	Ridesharing partner, 0 if general public matching, 1 if coworker or neighbor	+0.222	2.58	+0.216	2.21	+0.138	2.00	+0.081	1.41
WS	Work schedule, 0 if flexitime, 1 if fixed 8-h day	+0.401	4.66	+0.384	3.94	+0.581	8.46	+0.399	6.93
TT	Travel time (min)	-0.030	-2.77	-0.025	-2.27	-0.019	-1.89	-0.033	-3.70
Walk Utility (U_w)									
CW	Walk constant	0.386	4.46	0.268	2.820	0.151	2.30	0.119	2.01
WD	Walk distance to work (miles)	-0.897	-3.36	-0.936	-3.08	-0.925	-5.48	-0.784	-5.03
SW	Sidewalks, 0 if all the way, 1 if part of the way	0	-[a]	0	-[a]	0	-[a]	-0.053	-0.68
SN	Season, 0 if summer, 1 if winter	-0.756	-5.66	-0.750	-4.93	-0.868	-10.29	-0.848	-10.83
Bicycle Utility (U_b)									
CB	Bicycle constant	-0.275	-3.81	-0.130	-1.610	-0.225	-3.56	-0.418	-7.49
BD	Bicycle distance to work (miles)	-0.245	-5.24	-0.213	-3.67	-0.254	-6.69	-0.276	-8.19
BL	Bicycle lane, 0 if marked lane in street, 1 if no lane	-0.356	-3.81	-0.216	-1.87	-0.330	-4.27	-0.296	-4.40
SS	Street surface, 0 if smooth, 1 if rough	-0.383	-4.11	-0.470	-4.05	-0.431	-5.57	-0.400	-5.93
TR	Traffic, 0 if quiet, 1 if busy	-0.517	-5.53	-0.500	-4.31	-0.417	-5.39	-0.378	-5.61
Bus Utility (U_t)									
BT	Bus transfer time (min)	-0.044	-2.00	-0.035	-1.58	-0.019	-0.96	0	-[a]
BF	Bus fare ($)	-0.221	-0.81	-0.443	-1.58	-0.240	-0.96	-0.195	-0.88
HW	Bus headway (min)	0	-[a]	0	-[a]	-0.006	-0.84	-0.007	-1.14
TT	Travel time (min)	-0.030	-2.77	-0.025	-2.27	-0.019	-1.89	-0.033	-3.70
R^2		0.151		0.116		0.139		0.131	
F		21.44		14.24		32.56		38.73	
Data points		2440		2184		4272		5432	

[a]Coefficient was set to zero because the t-value was less than 0.3 and the wrong sign occurred.

Gasoline availability, gasoline price, and parking cost all have a significant effect on mode choice. A wait in line of between 5 and 20 min to purchase gasoline is less significant but has a stronger impact in small cities, where currently it may be more convenient to purchase gasoline and where there has been no previous experience with long queues to buy gasoline. Income and vehicles per person are generally significant also. This use of socioeconomic variables as additive terms in the automobile utility was chosen for simplicity and consistency across urban areas. The use of different socioeconomic specifications could improve the model goodness-of-fit somewhat but at the price of added complexity.

The travel time coefficients for drive alone, shared ride, and transit were constrained to be equal for consistency. Work schedule and ridesharing partner were both significant variables in the ridesharing utility.

The walk utility is strongly dependent on distance and season, but sidewalk availability was not perceived as a major factor, except by some respondents in the small cities, which have less extensive sidewalk systems. Bicycle utility also depends strongly on distance, but it also depends on the presence of a bicycle lane, street surface, and traffic levels. (Season was not included in the bicycle-automobile experiment, but the season coefficient from the walk model is used in the bicycle utility function for policy analyses.)

The bus utility equation (Equation 7) contains surprising results over the ranges of variables tested, which show strong sensitivity to overall travel time but relatively little to headway (15- to 30-min range) and fare (40- to 80-cent range). Transfer times of 0-5 min had a modest affect. Respondents may have had difficulty in assessing individual time components for a bus trip and, therefore, used the total time variable to determine their choice.

The city-to-city variations in the constants are as anticipated. Madison shows the highest propensity to use non-drive-alone modes, and other cities have lower constants in those cases. The R^2 of the regressions ranges from 0.116 to 0.151, which is expected given the lack of market segmentation, the inclusion of invariant respondents who indicated all 1s or all 5s on the survey, and the simple socioeconomic descriptions used. The F-statistics are all significant.

Calibration

In the calibration step of the analysis, the models built from stated behavior in the experiment are tested against actual, current behavior as a check. We substitute levels of independent variables that represent current conditions into the experimentally derived utility functions to obtain values of $\bar{U}_a$, $\bar{U}_s$, $\bar{U}_w$, $\bar{U}_b$, and $\bar{U}_t$ for each respondent. These values are then substituted into a logit formulation to test how well they explain current choice:

$$p_i = \exp(a_i+b_i\bar{U}_i)/\sum_{\text{all } j} \exp(a_j+b_j\bar{U}_j) \tag{2}$$

where

p_i = probability of a respondent choosing mode i (equal to 0 or 1 in actual data);
$\bar{U}_i$ = a respondent's computed utility value for mode i under current conditions, calculated from regression results; and
a_i, b_i = coefficients to be determined in logit estimation.

The equations below represent the regression results for Madison as five separate utility equations, as required for the validation. These separate equations sum to the original equation, with a negative sign for drive alone.

The linear utility equations for Madison from regressions on experimental responses are as follows: For automobile,

$$\begin{aligned} U_a = &-5.271 - \underset{(-6.30}{0.320GA} - \underset{-5.48}{0.234GP} - \underset{-6.93}{0.016PK} - \underset{-0.089}{0.008WT} \\ &+ \underset{6.02}{0.012IN} + \underset{3.12}{0.178VP} - \underset{-2.77)}{0.030TT} \end{aligned} \tag{3}$$

For shared ride,

$$U_s = \underset{(3.08}{0.216} + \underset{2.58}{0.222RD} + \underset{4.66}{0.401WS} - \underset{-2.77)}{0.030TT} \tag{4}$$

For walk,

$$U_w = \underset{(4.46}{0.386} - \underset{-3.36}{0.897WD} - \underset{-5.66)}{0.756SN} \tag{5}$$

For bicycle,

$$U_b = \underset{(-3.81}{-0.275} - \underset{-5.24}{0.245BD} - \underset{-3.81}{0.356BL} - \underset{-4.11}{0.383SS} - \underset{-5.53)}{0.517TR} \tag{6}$$

For local bus transit,

$$U_t = \underset{(-2.00}{-0.044BT} - \underset{-0.81}{0.221BF} - \underset{-2.77)}{0.030TT} \tag{7}$$

where

U_a = automobile utility,
GA = gasoline availability,
GP = gasoline price ($/gal),
PK = parking costs ($/month),
WT = wait time to buy gasoline (min),
IN = annual household income ($000s in 1980),
VP = vehicles per person $\geq$ 16 years old in household,
TT = travel time (min),
U_s = shared-ride utility,
RD = ridesharing partner,
WS = work schedule,
U_w = walk utility,
WD = walk distance to work (miles),
SN = season,
U_b = bicycle utility,
BD = bicycle distance to work (miles),
BL = bicycle lane,
SS = street surface,
TR = traffic,
U_t = bus utility,
BT = bus transfer time (min), and
BF = bus fare ($).

In order to gain some understanding of the values of a_i and b_i that indicated satisfactory correspondence between the experimental model and actual behavior, a simple analysis was performed. We know immediately, of course, that we wish all $b_i > 0$ and all a_i to be small in some sense. Figure 2 shows the hypothesized relation in a binary case between linear regression results and the binary logit equation. If stated behavior (linear model) corresponds to actual behavior (logit model), then we expect the linear utility equations to perform well in the logit model. A linear approximation tangent to the logit function at p = 0.5 (as drawn) has a slope of 0.25 and thus intersects the p = 0 and p = 1 axis at U = -2 and U = +2, respectively. This scale, from -2 to +2, is our 1-5 response scale shifted downward three units. We can expect b_j to

Figure 2. Comparison of linear and logit model forms.

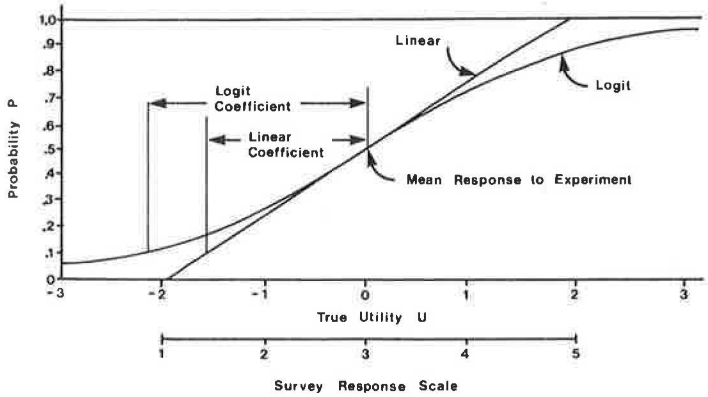

Table 2. Multinomial logit calibration results.

	Madison (n = 312)				Milwaukee County (n = 282)				Fox River Valley Cities (n = 661)				Other Cities (n = 873)			
	a		b		a		b		a		b		a		b	
Mode	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value
Drive alone	+13.221	3.13	+2.558	2.57	+5.166	1.17	+2.716	1.54	+12.437	1.94	+2.496	1.50	+7.942	2.21	+1.398	0.93
Rideshare	-1.510	-1.47	-0.404	-0.58	-17.173	-0.09	+3.419	0.06	-1.332	-1.02	+0.228	1.05	-1.308	-1.49	+1.600	0.62
Walk	+0.813	1.49	+2.39	3.29	+2.812	3.88	+2.758	2.78	+1.646	1.47	+2.211	4.15	+2.000	2.66	+3.108	6.21
Bicycle	-0.390	-0.60	+0.740	0.90	+1.525	1.10	+2.119	1.12	+0.347	0.30	+1.602	1.66	+1.403	1.64	+2.090	2.80
Bus	0.0	-[a]	+1.331	0.98	0.0	-[a]	+0.575	1.06	0.0	-[a]	+4.550	1.99	0.0	-[a]	+1.665	1.12

Note: The b coefficients are tested against the null hypothesis that b = 1, and the a coefficients are tested against the null hypothesis that a = 0, except for drive alone, where the null hypothesis is a = 3. The -2* log-likelihood ratio was 319.07 for Madison, 507.71 for Milwaukee County, 1032.53 for Fox River Valley cities, and 1246.10 for other cities.

[a]Coefficient was set to zero because the t-value was less than 0.3 and the wrong sign occurred.

approximately equal 1 and a_j to equal 0. The use of p = 0.5 as the point at which the approximation is made is justified by the experimental design, which can create sets of situations in which the alternatives are well matched.

In the multinomial case, the approximation will necessarily be centered at $p < 0.5$ for most modes; this implies that $b_j > 1$ because the lower slope of the logit curve at $p \neq 0.5$ produces a linear scale longer than four units between the p = 0 and p = 1 axes. We still expect all a_j to be 0 if there are no systematic biases across experiments, with one exception. (The a_j for automobile is expected to be +3 because automobile's position on the survey response scale is the reverse of the other modes.) One a_j must be set arbitrarily, so we set the bus a_j equal to zero; thus, the bicycle, walk, and shared ride a_j are also expected to be zero.

These arguments are intended only to give an approximate sense of the values of a_j and b_j to expect from the logit-estimation step. Furthermore, this calibration is approximate for the same reasons that limit our ability to estimate a revealed preference model for the study--lack of variability in several major variables, unavailability or low use of alternatives, multicollinearity, and other problems. Even so, it is important to attempt to calibrate the models to test their accuracy. Because we are estimating only two coefficients per mode in the validation (a_j and b_j), we may succeed in establishing them when trying to estimate all coefficients would fail.

Most data required for calibration were self-reported, although a few items were gathered from transportation planning data bases. Self-reported data were checked against planning data where possible, but the comparison was inconclusive because of the aggregation errors in the planning data (e.g., multiple bus lines in a zone, varying parking charges).

The calibration results appear in Table 2. We describe the calibration results for Madison in detail and briefly compare them with those of the other areas. (The number of respondents is higher than in the regression step because responses with incomplete experimental data could be used in this step.) The results show a very strong relation between the experimentally derived utilities and actual behavior, so we turn to an examination of the adjustment coefficients a_j and b_j. The coefficients a_j are tested against a null hypothesis of zero (+3 for drive alone), and b_j is tested against a null hypothesis of one.

The Madison drive-alone utility derived from the experiment apparently understates the sensitivity of actual behavior to the variable set, because the coefficient b_j is 2.558 and is significantly different from 1 at the 95 percent level of confidence. The adjustment in the constant a_j is not as large as it appears: The new constant is 13.221 + 2.558 (-5.271) or -0.262, as compared with the original value of -5.271. However, an adjustment of +3 was expected a priori. The adjustment in a is also statistically significant at a 95 percent level of confidence.

The ridesharing calibration is inconclusive. The only variables in its utility equation are the ridesharing partner (invariant in the sample, all being coworkers or neighbors), the work schedule (taking only two values), and the time (a fixed difference from automobile). Thus, there is little variability on which to relate the utility values to actual behavior. This mode is an extreme example of the difficulties in validating models. Neither a_j nor b_j is statistically different from the null hypothesis, which we fail to reject.

The walk mode has a coefficient b_j that is significantly different from 1; the calibrated constant is 0.813 + 2.39 (0.386) or 1.735. The bicycle mode's coefficients are quite close to their presupposed values, and the adjustments are not significant. The same holds for the bus mode.

In general, the coefficients for the other models follow the same pattern as the Madison coefficients. The calibration coefficients are larger than we would ideally like to see, but they indicate a relatively good correspondence between the experimental models and actual behavior. Coefficients that are different from the a priori values may also occur for a variety of reasons not related to the correspondence between stated and actual behavior--errors introduced by the linear approximation, errors in self-reported data, aggregation errors in planning data (believed to be significant in this case), and the simplicity of the socioeconomic description.

An examination of the results for the coefficient b_j suggests that we should use the calibration coefficients to revise all the walk utility functions, the Madison drive-alone utility, and the other cities' bicycle utility.

Table 3. Final models.

Variable	Milwaukee County	Madison	Fox River Valley Cities	Other Cities
Automobile utility				
Gasoline availability	-0.377	-0.320^a	-0.318	-0.315
Gasoline price	-0.320	-0.234	-0.284	-0.284
Parking cost	-0.017	-0.016	-0.017	-0.016
Wait time to buy gasoline	-0.004	-0.008	-0.013	-0.007
Annual household income	0.010	0.012	0.001	0.008
Vehicle per person ⩾ 16 years old in household	0.078	0.178	0.096	0.004
Travel time	-0.025	-0.030	-0.019	-0.033
Shared-ride utility				
Ridesharing partner	0.222	0.216	0.138	0.081
Work schedule	0.401	0.384	0.581	0.399
Travel time	-0.030	-0.025	-0.019	-0.033
Walk utility				
Walk distance to work	-2.581^b	-2.144^b	-2.045^b	-2.437^b
Sidewalks	0.0	0.0	0.0	-0.165
Season	-2.069	-1.807	-1.919	-2.636
Bicycle utility				
Bicycle distance to work	-0.213	-0.245	-0.259	-0.577^b
Bicycle lane	-0.216	-0.356	-0.330	-0.619
Street surface	-0.470	-0.383	-0.431	-0.836
Traffic	-0.500	-0.517	-0.417	-0.790
Season	-2.069	-1.807	-1.919	-2.636
Bus utility				
Bus transfer time	-0.035	-0.044	-0.019	0.0
Bus fare	-0.443	-0.221	-0.240	-0.195
Bus headway	0.0	0.0	-0.006	-0.007
Travel time	-0.025	-0.030	-0.019	-0.033

[a]Indicates b_j different from one, but original coefficients used based on sensitivity analysis.
[b]Indicates group of coefficients multiplied by b_j significantly different from one.

Sensitivity Analysis

Before selecting the final model coefficients, we used the incremental form of the logit model to perform sensitivity analysis:

$$p_i^1 = p_i \exp(\Delta U_i^*) / \sum_{\text{all } j} p_j \exp(\Delta U_j^*) \quad (8)$$

where

p_i^1 = revised share of mode i;
p_i = base share of mode i;
U_i^* = validated utility of mode $i = a_i + b_i U_i$, where a_i is significantly different from 0, and b_i is significantly different from 1; and
ΔU_i^* = change in the validated utility of mode j due to a change in a variable from the base case, ΔX.

The sensitivity analysis indicated that most of the validated models provided reasonable results. However, if predictions are made with the validated Madison drive-alone utility function, we find that a $0.60 increase in gasoline price from $1.30/gal causes the mode share for driving alone to decline from 56 to 45 percent, a reduction equal to 9 percent of all work trips. These results are outside the range expected on the basis of gasoline price elasticities reported in the literature. When we used the calibrated automobile utility function to predict the effect of changes in fuel availability and parking costs, we also obtained changes in market shares too large to be believable. Because of the possible confounding factors that could have produced a coefficient b_j different from one, we chose to retain the original experimental utility equation for Madison drive alone.

FINAL MODELS

The final models appear in Table 3. Only the walk models and the other cities bicycle model have been adjusted through the calibration step, as described above; the other models are in their original form based on the experiment. Only the Madison drive-alone model had a significant b_j but was not changed due to sensitivity results. All other models have also been tested in sensitivity analysis and produce reasonable results. Adjusted constants are not shown, as they are dependent on the level of aggregation used; a simple procedure is used to find base values of the constants when the models are applied for forecasting.

Table 4 gives the elasticities and values of time that emerge from the final models. The values generally agree with the previous literature, although the range of variation is outside that of past data and creates some differences.

The results of this effort highlight some key

Table 4. Selected elasticities and values of time.

	Direct Elasticities				Cross Elasticities[a]		
Urban Area	Gasoline Price	Parking Cost	Bus Fare	Bus Travel Time	Gasoline Price	Parking Cost	Marginal Value of Time[b] ($/h)
Milwaukee County	-0.166	-0.059	-0.247	-0.349	+0.448	+0.186	4.64
Madison	-0.196	-0.106	-0.117	-0.396	+0.249	+0.134	7.69
Fox River Valley	-0.152	-0.071	-0.141	-0.279	+0.387	+0.183	4.01
Other cities	-0.183	-0.082	-0.189	-0.480	+0.356	+0.158	7.15

Note: All elasticities are point elasticities and were calculated at the mean value of the independent variables in the experimental data sets: gasoline price = $1.90/gal, parking cost = $15/month, bus fare = $0.60, travel time = 15 min.
[a]Logit models have constant cross elasticities (i.e., for a 1 percent change in gasoline price, for example; all other modes have the same change in demand).
[b]Marginal values of time calculated by using the travel time and the gasoline price coefficients.

issues in integrating functional measurement and disaggregate models. When using functional measurement to address issues not well captured in data on actual behavior, testing of the correspondence between stated and actual behavior is difficult. The standard validation approach of simple prediction of mode shares with the functional measurement model and comparison to aggregate actual shares is sensitive to the values of the independent variables assumed (and about which there is some latitude) and generally does not yield statistical measures of the closeness of correspondence (9). This study attempted to assess whether functional measurement models could be used in a logit framework without adjustment and whether sufficient variability existed to check the performance of the model. The results are encouraging, although more work is clearly needed.

MODEL APPLICATIONS

These models are currently in use in several functions at WisDOT. First, they are being used in their incremental logit form for statewide policy-level analysis of key issues that face the department. By comparing the impacts of state policies in a consistent fashion across Wisconsin urban areas, the department can target its programs where their effect is largest. A policy report has been prepared based on the models (10) and concludes, for instance, that transit assistance should be targeted at larger urban areas where its effect is significant, that ridesharing should be promoted in all areas, with an emphasis on employer and neighborhood matching programs versus less-effective general public matching programs, and that bicycle lanes may be cost-effective investments for diverting travelers from driving alone, even though their impact is only seasonal. In many cases bicycle lanes have greater impacts than transit improvements and lower cost. In Madison, for example, if bicycle lanes were marked on the streets in a corridor where the percentage of people that use each mode to work equaled each mode's share for the city as a whole, drive alone's share of the work trips would decrease by almost 3 percent. In contrast, a 5-min reduction in bus transfer time would divert less than 2 percent of the total trips from drive alone and a 10-min reduction in bus travel time would decrease drive alone's share by only 1 percent. The direction for transit improvements, when considered alone, will involve decreases in travel time and fare increases, as service level generally appears more important than fare to the public over the ranges examined.

Some of the more interesting conclusions and policy implications of the study include the following. Approximately 112 000 of 1.5 million one-way daily home-bound work trips would switch from driving alone to other modes if gasoline were rationed (10 gal/registered vehicle each week). A wait of 30 min to buy gasoline at a service station would cause 70 000 of the 1.5 million daily drive-alone trips to shift to other modes.

The models reported here indicate that a general public carpool matching program is not as effective as an employee or neighborhood-based ridesharing programs in Wisconsin cities larger than 50 000 people. However, a similar set of models for long-distance commuter travel between Madison and its satellite communities indicate that residents of villages and small communities in rural areas are nearly as willing to share rides with strangers as with neighbors or coworkers. Fear of strangers seems to be more prevalent in larger cities than in small rural communities, as expected. Thus, a general public carpool matching program might work well for commuters who live in small communities outside Wisconsin's larger cities. Universal flexitime for workers in the urban areas studied would cause 58 000 fewer home-based work trips by ridesharing to occur daily than if everyone worked fixed 8-h shifts.

The addition of marked bicycle lanes to all streets throughout each of the cities studied would encourage an additional 26 000 bicycle work trips in good weather months, a 39 percent increase in total summertime bicycle trips. Bicycle lanes would impact strongly on bicycle ridership in the medium and smaller cities of Wisconsin but would have little effect in the state's largest city, Milwaukee. The allowing of pavements throughout 10 cities to deteriorate from smooth to rough riding surfaces would cause a reduction of 38 000 bicycle work trips on nice days--a 42 percent reduction in total bicycling in the summertime. Thus, local street maintenance practices should pay particular attention to keep pavements on popular bicycle routes in good condition to avoid loss in bicycle ridership.

The models are also being made available to urban areas for use in their planning process. They can be implemented in the urban transportation planning system (UTPS) as part of WisDOT's technical assistance role to local areas. These models will lead to more detailed, yet consistent, evaluations of policies already assessed at a statewide level by incremental logit.

Finally, the models have a quick-response capability through the use of incremental logit and are available to respond to requests by planning and other agencies for quick analyses of proposed services and policies. A major staff capability exists at WisDOT to use these models in this manner.

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The analysis, results, conclusions, and recommendations are solely ours and do not necessarily represent the views or policies of WisDOT.

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Elasticity-Based Method for Forecasting Travel on Current Urban Transportation Alternatives

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This paper presents a quick-response incremental travel demand forecasting method that uses travel demand elasticities and readily available ground count travel and land use data. Elasticities are defined and criteria for selecting elasticities are identified. The steps for calculating each component of travel affected by a transportation improvement are described. Personnel and computational requirements for this method are greatly reduced relative to those necessary for forecasting with the conventional four-step sequential process (trip generation, distribution, modal split, and trip assignment). The basic travel behavior assumptions of the method are similar to those inherent in conventional models although, in contrast to sequential derivation and application of these models, internally consistent causal relations are maintained. A range of outputs of interest to policymakers is generated, including changes in total travel, changes in mode-specific travel, and changes in travel on a given route or link. The elasticity-based method has recently been used to forecast patronage on the four major transit alternatives included in the Baltimore North Corridor alternatives analysis. This application is described in the paper and compared with forecasts made in a particular application of the conventional four-step sequential travel demand forecasting system for the same alternatives under the same conditions. This direct comparison of the two forecasting methods provides a unique opportunity to assess the effects on forecast patronage of many assumptions inherent in typical applications of each method.

Much of the concern over urban travel demand forecasting involves the turnaround time and expense of applying existing conventional sequential travel demand models. Also, application of these conventional models often involves a series of restrictive assumptions that can reduce severely their ability to distinguish travel impacts between alternatives (1). These models synthesize travel patterns from scratch based on a long list of land use, socioeconomic, and level-of-service variables, which themselves must be forecast (thus propagating errors) (2). One way to cut significantly the large costs currently associated with urban travel forecasting is to use elasticities with respect to those limited numbers of variables related to the policy option of interest. Also, since elasticities can be behavioral, the spatial extent of the forecasts can be limited to those areas of the region affected by the system change being tested. The most easily available travel data, namely ground count data, can be factored incrementally at some useful and informative level of aggregation. Such an approach saves the time, expense, and uncertainty involved in forecasting and calculating entire sets of independent variables.

The elasticity-based approach described here has recently been used to forecast patronage on four major transit alternatives considered in the Baltimore North Corridor alternatives analysis. In addition to the elasticity-based forecasts, patronage estimates were developed by the Baltimore Regional Planning Council by using the existing four-step, sequential forecasting system estimated with urban transportation planning system (UTPS) software. Hence, the opportunity to compare and evaluate the two methods was provided.

ELASTICITIES

A travel demand elasticity is defined as the percentage change in ridership or traffic volume (depending on what is measured) that results from a 1 percent change in a given independent variable (e.g., travel time or cost) (3). Elasticities are measures of the partial effect on travel of changes, taken singly, in the travel environment that confront travelers. They allow shifts in travel patterns to be estimated at the margin in response to changes in the travel environment and, therefore, existing observed travel unaffected by changes is preserved. Existing synthetic (UTPS) procedures can only duplicate existing travel with some difficulty.

Elasticity-Based Forecasting Method

The elasticity-based forecasting procedure is based on the concept that travel on a new or improved transit facility is composed of four components, each of which results from one mutually exclusive cause or behavior and each of which can be calculated separately and sequentially to include the results of the previous change. The four components are as follows:

1. Transit travel that does not exist today due to growth in numbers of people and jobs; these are changes in travel due to so-called long-run demand, or land use changes;
2. Transit travel that is diverted from (or to) the automobile mode due to changes in automobile-operating costs (e.g., increases in gasoline price) and other automobile level-of-service changes (e.g., reductions in travel time due to highway construction);
3. Transit travel diverted to the improved transit facility from transit facilities for which the new or improved transit facility is a superior substitute; this is diverted travel from facilities of the same mode; and
4. Induced transit travel, or travel that is induced in the corridor and specifically on the transit alternative being evaluated as a result of the new or improved transit facility; induced transit travel includes travel that results from increased rates of choice of destinations served by the improved facility and increased transit trip