Predictive Models of the Demand for Public Transportation Services Among the Elderly

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Models for accurately predicting the travel demands of the elderly are in their infancy. After reviewing the advantages and disadvantages of disaggregate behavior models and of aggregate models, this paper reviews a series of specific aggregate demand models that include service specifications. Both urban and rural models are developed. The results of ordinary least-squares and two-stage least-squares regression methods are compared for their predictive capabilities and agreement with previous findings; both formats are found to have some advantages. Specific models combine high predictive capabilities with generally accepted elasticities of the component variables. These models are ready for immediate application.

Specialized services for transporting the elderly and handicapped have become a major focus of current transportation planning activities. Section 5 of the Urban Mass Transportation Act of 1974 requires reduced transit fares for the elderly and handicapped as a condition for federal transit operating assistance. Federal regulations also require full consideration of these groups in transit system design and operation.

This new emphasis has illuminated several gaps in our knowledge of appropriate systems. In particular, apart from evaluation studies (1,2) on the effect on demand of reduced fares for the elderly, there has been a dearth of research on demand elasticities and demand predictive models for transportation services for elderly travelers. Caruolo's compilation of studies of reduced fares (1) shows that travel by the elderly is fairly inelastic; the average fare elasticity is -0.38. However, no comparable elasticities are available for service specifications such as frequencies, reservation times, and other characteristics of transportation services. The study on which this paper is based was undertaken to estimate demand elasticities for public transportation services among the elderly and in the process to develop simple demand models that could be applied to a variety of rural and urban scenarios for predicting transportation demand of the elderly.

DEMAND MODELS

Two basic sets of mode-choice models appear in the literature: the disaggregate or individual trip models (3,4) and the aggregate or traffic-zone-group models (5-7).

Disaggregate Behavioral Models

Disaggregate (quantal dependent variable) models are characterized by the analysis of dependent variables that represent a single occurrence such as a trip. The disaggregate models are called behavioral models because they may be derived by postulating a utility-maximizing behavior on the part of household trip makers. In these models, the household is pictured as estimating the potential net utility derived from making a trip (a trade-off of the disutility derived from the effort and cost involved in making the trip versus the utility derived at the trip destination) and as examining the full range of alternative choices available before actually making a decision to travel.

Although the development of the disaggregate behavioral models has been a significant addition to the transportation-demand-analysis literature, the temptation to oversell these worthwhile models has been irresistible. The fact is that there are good and sensible disaggregate models that have reasonable travel elasticity values, as well as unreasonable models that have elasticity values beyond the level experienced in the price and service demonstrations conducted by the Office of Service and Methods Demonstration of the Urban Mass Transportation Administration (UMTA).

In spite of the popularity of the disaggregate behavioral model, the last year or so has witnessed an attempt at a reappraisal of these models. In a recent article, Oum (8) has shown that the linear multinomial logit models (a) impose many rigid a priori conditions on the elasticities and cross elasticities of demand, (b) result in estimates of elasticities that are not invariant to the choice of the base or modal denominators, and (c) possess severely irregular and inconsistent underlying preference or utility structures. Oum argues for a careful and sensible use of the logit models and for a de-emphasis of some of the ambitious and extravagant claims made about their theoretical superiority. Oum argues, for example, that elasticities should not be computed from these models and that their use should be restricted to standard applications.

To Oum's reservations we must add some of our own. In spite of their claim to be utility-related behavioral models, none of these models is formally derived by maximizing utility functions. Furthermore, the conventional economic theory approach to demand analysis, which places the price variable and the time variables in monetary budget and in time constraints, respectively, is disregarded in the "utility" approach. Finally, and more important, both Theil (9) and Nerlove and Press (7) argue that simultaneous choices--such as the choice of more than two transport modes--cannot be estimated by means of single-equation estimation techniques such as the maximum likelihood approaches currently being used by the transportation mode-choice modelers, since to do this would result in biased coefficients in the estimated models.

Aggregate Models

In aggregate models, the dependent variable represents a group of observations in which individual trip data are grouped into traffic zones. The major criticism of these models as compared with disaggregate models is their statistical inefficiency (aggregate models need more data to obtain a fixed confidence level).

This paper presents the development of aggregate direct demand models, whose internal structure is of the Cobb-Douglas type. These demand models estimate ridership directly without requiring any aggregation process. The choice of an aggregate direct demand model was dominated by considerations of data availability. The basic data used to estimate the models consist of a survey of the total passengers transported and the service specifications of 335 transportation projects that served the elderly during 1976. These projects responded to a mail survey of projects funded by the Administration on Aging of the U.S. Department of Health, Education, and Welfare (HEW) and by UMTA. Because the survey--to ensure high response rates--contained no questions on trip purposes or on origin-destination patterns, the direct demand analysis that follows focuses on aggregate travel data. Thus, it is impossible to apply disaggregated behavioral trip-making models (3), which require a more refined and specific trip-purpose data base.

AGGREGATE DIRECT DEMAND MODEL

Formulation

The demand schedule for elderly travelers' use of public transportation services (both regular and specialized bus services) conveys information on the amount of passenger ridership attracted by a transportation project or system as a function of fare charges and the level of service offered by the system, as well as the ridership attracted by its competing services.

Essentially the demand model specifies that the number of riders attracted by a transportation service depends on several factors, such as

1. Need or potential market--represented by the number of the elderly in the service area or the number of elderly poor;
2. Specifications of transportation services--represented by frequencies for fixed-route systems, reservation times for demand-responsive systems, and fares and bus miles for fixed-route and demand-responsive systems;
3. Linkage to other social services programs--represented by whether the transportation service transports elderly passengers to the nutrition project sites or to similar sites for the delivery of social services;
4. Competing transportation services--represented by the existence of another transit-type service or a large or medium-large social-service-related transportation system that serves the same service area; and
5. Service-area characteristics--represented by whether the service area is urban or rural and by its residential densities.

The elements that affect demand for bus transportation services for the elderly may be summarized in the following function:

$$\begin{aligned}\log \mathrm{ELDPASS}_i = {} & b_0 + b_1 \log(\mathrm{ADBUSMILES}_i) + b_2 \log(\mathrm{ELDPOP}_i) \\ & + b_3 \log(\mathrm{ELDPOOR}_i) + b_4 \log(\mathrm{FARES}_i) \\ & + b_5 [(\mathrm{FR}_i) \times \log(\mathrm{FREQ}_i)] \\ & + b_6 [(\mathrm{DR}_i) \times \log(1/\mathrm{RESTIME}_i)] + b_7 (\mathrm{COMP}_i) \\ & + b_8 (\mathrm{NUTR}_i) \end{aligned} \tag{1}$$

where

$\mathrm{ELDPASS}_i$ = one-way elderly passenger trips per month for system i;
$\mathrm{ADBUSMILES}_i$ = adjusted monthly vehicle miles operated to serve elderly passengers [computed by multiplying the regular monthly bus miles by the proportion of elderly passengers out of total passengers, as in $\mathrm{ADBUSMILES}_i = (\mathrm{ELDPASS}_i/\mathrm{PASS}_i)(\mathrm{BUSMILES}_i)$, where PASS_i = total passengers (elderly and nonelderly) for system i and $\mathrm{BUSMILES}_i$ = total monthly bus miles for system i; this procedure was necessary because some of the transportation projects analyzed served other target groups as well];
ELDPOP_i = elderly population in the service area covered by transportation system i (thousands of persons);
$\mathrm{ELDPOOR}_i$ = elderly population in the service area covered by system i who are poor (numbers of persons);
FARES_i = one-way elderly-passenger fares per trip for system i (cents);
FR_i = 1 if the system i is a fixed-route system, 0 if not;
DR_i = 1 if the system i is a demand-responsive system, 0 if not;
FREQ_i = average round trips per month for system i (in the case of a demand-responsive system, the frequency variable is 0);
$\mathrm{RESTIME}_i$ = system design specification for reservation time (days) (measures the days in advance that the user must reserve the use of the system);
COMP_i = 1 if system i is in competition in its service area with a transit service or with a social-service-related transportation system that carries more than 2500 elderly passengers monthly, 0 if not; and
NUTR_i = 1 if transportation services to nutrition sites amount to at least 10 percent of the elderly-passenger trips in urban areas, 0 if not (in rural areas, this variable was assigned a value of 1 if services to a nutrition site were delivered by transportation system i, 0 if not).

The variable definitions shown above present two alternative need variables--the elderly population and the elderly poor. The elderly population is a more general estimate of need since it includes the elderly who have physical or health barriers to mobility, a status that is not necessarily correlated with income. For example, the simple correlation of elderly residents' personal income with restrictions on mobility is only -0.12 among the elderly in Houston, Texas (10), which indicates that to define the elderly who need transportation assistance solely on the basis of income excludes numerous people who need such services. The rural elderly who have restrictions on mobility includes from 15 to 25 percent of the rural elderly, depending on the region of the country (11,12). Both of these concepts of need will be investigated in this paper.

One of the problems associated with the demand function presented in Equation 1 is the uncertainty surrounding the definition of the bus mileage variable as an independent variable. Although it is true that bus miles are not the proper supply variable (which is actually seat miles), there are still significant connotations of supply associated with this bus mileage variable.

Three direct demand models are presented in this paper:

1. An ordinary least-squares model that assumes that bus mileage is an independent variable;
2. A "reduced-form" model, also estimated through ordinary least squares, that postulates that the bus mileage variable is endogenous or jointly dependent; and
3. A simultaneous-equation model of demand and supply estimated through two-stage least-squares estimation methods.

Table 1. Regression analysis results of demand for 163 transportation systems that serve the rural elderly.

Rural Regression Equation	Evaluation Statistic	Independent Variable: Intercept (constant)	log $ELDPOP_i$	log $ADBUSMILES_i$	log $FARES_i$	$COMP_i$	$(FR_i) \times \log (FREQ_i)$	$(DR_i) \times \log (1/RESTIME_i)$	$NUTR_i$	log $ELDPOOR_i$
1	Regression coefficient	−0.251	0.164	0.786	0.023	−0.155	0.087	0.105	0.291	
	Standard error		0.078	0.082	0.060	0.069	0.045	0.044	0.069	
	F value		4.452	90.885	0.145	4.993	3.587	5.690	17.601	
2	Regression coefficient	−0.248	0.167	0.786		−0.159	0.088	0.107	0.287	
	Standard error		0.077	0.082		0.068	0.045	0.043	0.068	
	F value		4.705	91.945		5.386	3.795	6.187	17.657	
3	Regression coefficient	2.061	0.591			−0.241	0.190	0.063	0.466	
	Standard error		0.079			0.085	0.055	0.053	0.082	
	F value		55.946			8.006	11.675	1.371	31.920	
4	Regression coefficient	−0.567		0.800		−0.131	0.083	0.109	0.287	0.121
	Standard error			0.081		0.065	0.045	0.043	0.068	0.064
	F value			95.340		3.989	3.274	6.149	17.446	3.573
5	Regression coefficient	0.953				−0.150	0.171	0.076	0.466	0.478
	Standard error					0.082	0.056	0.055	0.084	0.067
	F value					1.861	9.089	1.861	30.880	51.180

Note: R^2 values are 0.694 for Equation 1, 0.693 for Equation 2, 0.514 for Equation 3, 0.691 for Equation 4, and 0.503 for Equation 5.

Table 2. Ordinary least-squares demand models for 172 transportation systems that serve the urban elderly.

Urban Regression Equation	Evaluation Statistic	Independent Variable: Intercept (Constant)	log $ELDPOP_i$	log $ELDPOOR_i$	log $ADBUSMILES_i$	log $FARES_i$	$COMP_i$	$(FR_i) \times \log (FREQ_i)$	$(DR_i) \times \log (1/RESTIME_i)$
1	Regression coefficient	−0.063	0.100		0.940	−0.069	−0.217	0.173	0.035
	Standard error		0.048		0.042	0.034	0.049	0.020	0.033
	F value		5.031		479.764	4.056	18.982	72.022	1.065
2	Regression coefficient	2.655	0.817			−0.104	−0.478	0.294	0.257
	Standard error		0.060			0.068	0.095	0.038	0.064
	F value		182.876			2.352	25.109	57.893	16.194
3	Regression coefficient	−0.292		0.083	0.954	−0.069	−0.209	0.171	0.032
	Standard error			0.041	0.041	0.034	0.049	0.020	0.034
	F value			3.803	534.893	3.803	17.817	70.522	0.854
4	Regression coefficient	0.875		0.774		−0.098	−0.442	0.296	0.259
	Standard error			0.062		0.071	0.099	0.040	0.067
	F value			153.074		1.904	19.656	53.126	14.932

Note: R^2 values are 0.936 for Equation 1, 0.752 for Equation 2, 0.935 for Equation 3, and 0.728 for Equation 4.

Each of these models is described after a short discussion of the data base.

Data Base

To estimate the demand models already formulated, a data base that covered the ridership and operation characteristics of 335 transportation companies and transportation projects that serve the elderly had to be developed. The data were collected through a mail survey, conducted during the spring and summer of 1976, of projects funded by UMTA and HEW. Some of these systems served only the rural elderly; others accepted nonelderly passengers as well. However, all the systems served trips of several purposes, such as shopping, personal business, health, work, and social services trips; that is, the systems in the data base do not include those HEW-funded projects that serve only social trip purposes. The following text table presents an enumeration of the systems included in the data base. Some projects that included both fixed-route and demand-responsive components have been classified in this table according to their larger system component.

Type of System	Number of Projects: Rural	Urban
Fixed-route	43	111
Demand-responsive	120	61
Total	163	172

ESTIMATION OF SINGLE-EQUATION AND REDUCED-FORM DIRECT DEMAND MODELS

This section discusses the estimation of direct demand models by means of single-equation ordinary least-squares regression methods. Two types of models are estimated: (a) the reduced form, which suppresses the bus mileage variable from the regressions, and (b) the ordinary direct demand model, which includes bus miles as an independent variable. The discussion proceeds first with the demand models for the rural elderly, which are presented in Table 1, followed by the demand models for the urban elderly in Table 2. Note that all the logarithmic transformations presented in Tables 1 and 2 are expressed in base-10 logs, the variables are those previously cited, and the dependent variable is log $ELDPASS_i$.

The most promising rural demand functions appear in Table 1. Three of the functions (rural regression equations 1, 2, and 3) use the elderly population as a demographic variable; in equations 4 and 5 this variable has been replaced by the elderly poor.

The best rural regression equation is 2, which exhibits significant regression coefficients for all the variables and the second-highest R^2. Although equation 1 shows a higher R^2, it also exhibits statistically insignificant fares, which is its main drawback. In fact, the lack of statistical significance of the fares variables is the only disappointing result in the rural transportation demand functions. All the other explanatory variables--elderly population, vehicle mileage, frequencies of service, reservation times, and linkages to nutrition sites--are significant and have the right signs. Rural regression equations 2 and 3 in Table 1, which include ($ELDPOP_i$), outperform in terms of R^2 equations 4 and 5, which include the alternative variable ($ELDPOOR_i$).

Rural regression equations 3 and 5 of Table 1 denote the reduced-form demand equations, in which the vehicle mileage variable is suppressed. These reduced-form demand equations exhibit higher demand elasticities but at a cost of lower R^2 than those equations that contain supply variables. As stated earlier, the best rural equation is the second one, which explains 70 percent of the variance of the passenger experience in the 163 rural transportation systems analyzed.

The most promising ordinary least-squares demand models for the urban elderly appear in Table 2. Urban regression equations 2 and 4 present the reduced-form models; the other urban regression equations represent the ordinary demand model that has supply elements. Because of the colinearity between the ELDPOP and the ELDPOOR variables, these variables are run separately. The best ordinary demand model that has supply elements is urban regression equation 1; the best reduced-form model is urban regression equation 2. These two models outperform others in terms of goodness of fit and statistical significance of the regression coefficients.

Comparison of reduced-form models with the ordinary models that have supply elements reveals that the reduced-form equation, although it exhibits lower R^2s, also increases the statistical significance of some variables, such as the reservation times. In addition, the demand elasticities are higher in magnitude in the reduced-form models. As will be seen later, the elasticities of the reduced-form models are in general agreement with those estimated for the general population by other researchers (6,13,14).

SPECIFICATION AND ESTIMATION OF SIMULTANEOUS-EQUATION MODELS

The problem of including a supply variable (such as vehicle miles) among the independent variables of the demand analysis has been discussed briefly earlier. This problem results from the fact that the patronage of the system and its supply of bus miles are jointly dependent variables.

Jointly dependent variables are those variables that are mutually interdependent so that one affects the other and vice versa, e.g., the passenger variables and the vehicle-miles variable. It is obvious that variations in vehicle mileage affect the patronage of a given system; that is, patronage depends on, among other things, the vehicle mileage supplied. On the other hand, the service provider (whether city transit, private transit company, or social welfare agency) decides on the level of vehicle mileage to supply based on the strength of its expectations of the patronage that the provider can attract. Thus, vehicle mileage also depends on the patronage of the system. As a consequence, both vehicle mileage and patronage may be labeled as jointly dependent variables.

This simultaneity or joint dependency arises as a result of the presence of supply variables (vehicle miles) in the demand curve. In the presence of the jointly dependent variables, ordinary least-squares models result in biased regression coefficients, and thus unbiased simultaneous-equation estimation methods must be applied (15). To resolve the problem of joint dependency of bus mileage and passenger volumes, a simultaneous-equation model was estimated.

The structure of this simultaneous-equation model contains a demand function:

$$\begin{aligned}\ln(\mathrm{ELDPASS}_i) = {} & a_0 + a_1 \ln(\mathrm{ADBUSMILES}_i) + a_2 \ln(\mathrm{ELDPOP}_i) \\ & + a_3 \ln(\mathrm{ELDPOOR}_i) + a_4 \ln(\mathrm{FARES}_i) \\ & + a_5 [(\mathrm{FR}_i) \times \ln(\mathrm{FREQ}_i)] + a_6 [(\mathrm{DR}_i) \times \ln(1/\mathrm{RESTIME}_i)] \\ & + a_7 (\mathrm{COMP}_i) + a_8 (\mathrm{NUTR}_i)\end{aligned} \quad (2)$$

and a supply function:

$$\begin{aligned}\ln(\mathrm{ADBUSMILES}_i) = {} & b_0 + b_1 \ln(\mathrm{ELDPASS}_i) + b_2 \ln(\mathrm{ELDPOP}_i) \\ & + b_3 \ln(\mathrm{ELDPOOR}_i) + b_4 \ln(\mathrm{FARES}_i) \\ & + b_5 [(\mathrm{FR}_i) \times \ln(\mathrm{FREQ}_i)] \\ & + b_6 [(\mathrm{DR}_i) \times \ln(1/\mathrm{RESTIME}_i)] \\ & + b_7 (\mathrm{PRIVATE}_i) + b_8 \ln(\mathrm{POPDEN}_i)\end{aligned} \quad (3)$$

where $PRIVATE_i$ = 1 if transportation is provided by a private system and 0 if not, and $POPDEN_i$ = population density in the service area, measured in persons per square mile. The use of the term "ln" in Equations 2 and 3 denotes that natural (Naperian) logarithmic transformations were used on most variables. This change from base-10 logs to natural logs had to be made because the two-stage least-squares regression program used accepted only natural logs.

The specification of the demand curve is identical to the previous specification presented earlier. Increases in demographic variables, in vehicle mileage, and in service specifications (such as greater frequencies and shorter reservation times) are expected, on a priori grounds, to lead to increases in patronage by the elderly. However, the increases in numbers of elderly passengers will be less than proportional, so that demand elasticities lower than 1.0 are expected. Increases in fares and competition with other systems are expected to lead to less than proportional reductions in the numbers of elderly passengers.

The supply curve is more difficult to specify, partly because of the lack of data available on costs of supplying the transportation services. Because of the lack of available data on costs for the different systems, a new variable ($PRIVATE_i$) has been defined as a supply variable. The expectation is that private systems are more subject to the market discipline and thus strive for more efficient operation. This higher private-system efficiency translates into lower unit costs, lower ratios of vehicles miles per passenger, or both. To the extent that private systems exhibit higher efficiency, the introduction of the $PRIVATE_i$ variable will assist in the specification of the supply curve. The supply function specifies that the greater the expected patronage, population to be served, frequency, and reservation times, the greater the supply of vehicle mileage. The higher the fares, the greater the supply; if the system is private, a lower level of vehicle miles will be supplied. In both supply and demand functions, the $ELDPASS_i$ and $ADBUSMILES_i$ variables are specified as jointly dependent or endogenous variables; all the rest of the variables are specified as independent.

The above simultaneous-equation model was estimated by means of two-stage least squares. The two-stage least-squares model (15) used all the predetermined variables in the system in order to estimate a jointly dependent variable, and the predicted value of the jointly dependent variable was introduced among the independent variables of the regression. An example will suffice. In the case of estimating the demand function (Equation 2), first the jointly dependent $ADBUSMILES_i$ variable was estimated as a function of all the other independent or predetermined variables. Next the

Table 3. Two-stage least-squares simultaneous-equation models of transportation demand and supply for the rural and urban elderly.

Explanatory Variable	Model 1 Regression Coefficient	Model 1 Standard Error[a]	Model 2 Regression Coefficient	Model 2 Standard Error[a]
Demand Function for the Rural Elderly[b]				
Intercept (constant)	0.045	1.559	-0.550	1.270
ln $ADBUSMILES_i$	0.695	0.229	0.627	0.277
ln $ELDPOP_i$	0.216	0.139		
$(FR_i) \times \ln(FREQ_i)$	0.101	0.053	0.102	0.054
$(DR_i) \times \ln(1/RESTIME_i)$	0.102	0.045	0.102	0.046
$COMP_i$	-0.388	0.166	-0.310	0.153
$NUTR_i$	0.709	0.194	0.749	0.210
ln $ELDPOOR_i$			0.198	0.134
Supply Function for the Rural Elderly[c]				
Intercept (constant)	5.277	0.573	3.138	0.392
ln $ELDPASS_i$	0.313	0.096	0.308	0.100
ln $ELDPOP_i$	0.471	0.080		
$(FR_i) \times \ln(FREQ_i)$	0.165	0.058	0.143	0.058
DR_i	0.465	0.195	0.468	0.199
$PRIVATE_i$	-0.249	0.321	-0.197	0.331
ln $POPDEN_i$	-0.157	0.050	-0.105	0.046
ln $ELDPOOR_i$			0.381	0.067
Demand Function for the Urban Elderly[b]				
Intercept (constant)	-0.631	1.949	-0.831	0.687
ln $ELDPOP_i$	0.044	0.226		
ln $ADBUSMILES_i$	1.013	0.293	1.010	0.223
$(FR_i) \times \ln(FREQ_i)$	0.164	0.042	0.164	0.035
$(DR_i) \times \ln(1/RESTIME_i)$	0.018	0.078	0.018	0.063
$COMP_i$	-0.453	0.216	-0.451	0.168
ln $FARES_i$	-0.067	0.036	-0.067	0.035
ln $ELDPOOR_i$			0.043	0.164
Supply Function for the Urban Elderly[c]				
Intercept (constant)	3.619	0.763	2.081	0.591
ln $ELDPASS_i$	0.495	0.139	0.427	0.178
ln $ELDPOP_i$	0.329	0.109		
$(FR_i) \times \ln(FREQ_i)$	0.008	0.059	0.026	0.074
$(DR_i) \times \ln(1/RESTIME_i)$	0.116	0.056	0.131	0.066
$PRIVATE_i$	-0.238	0.167	-0.331	0.205
ln $POPDEN_i$	0.004	0.048	0.013	0.053
ln $ELDPOOR_i$			0.355	0.129

[a] The F-test was not computed for each regression coefficient because it is not available from the Time-Series Processor computer program used in estimating the two-stage least-squares regression.
[b] Dependent variable = ln $ELDPASS_i$; R^2 values are 0.691 for rural model 1, 0.683 for rural model 2, and 0.935 for urban models 1 and 2.
[c] Dependent variable = ln $ADBUSMILES_i$; R^2 values are 0.715 for rural model 1, 0.702 for rural model 2, 0.876 for urban model 1, and 0.849 for urban model 2.

predicted value of $ADBUSMILES_i$ was substituted back into Equation 2 in lieu of the original $ADBUSMILES_i$ variable, and Equation 2 was estimated by using ordinary least squares. This procedure, called two-stage least squares, results in unbiased although inefficient estimates, which lose their minimum variable properties (15).

Analysis of Transportation Demand and Supply for the Rural Elderly

The results of the two-stage least-squares regressions appear in Table 3. Rural model 1 defines need in terms of the total elderly population, whereas model 2 uses the number of elderly poor as a proxy for need. A close examination of both supply and demand functions reveals that ELDPOP is superior to ELDPOOR as an explanatory variable, as supported by the higher R^2 and statistical significance of the functions.

All the demand elasticities presented in Table 3 appear with appropriate signs and orders of magnitude, showing demand elasticities lower than 1.0 in absolute values. These demand elasticities may be contrasted with the previous elasticities estimated through ordinary least squares in Table 1. The effect of the two-stage least-squares estimation is to increase the elasticities of all the variables except $ADBUSMILES_i$, the supply variable whose elasticity is depressed by the two-stage least-squares technique.

In contrast with the demand curve, the supply-curve estimation leaves a lot to be desired, partly because of the lack of cost data in its specification. The variable that identifies private ownership of the system is statistically insignificant, and the sign of the DR_i variable is contrary to expectations. Contrary to first impressions, the sign of the population density variable is correct in the supply elasticities. However, more work is required, particularly in the area of costs, before a supply curve is successfully estimated for transportation projects for the rural elderly. The function derived may be interpreted as just a first approximation.

Analysis of Transportation and Supply for the Urban Elderly

The results of the application of the two-stage least-squares model to the transportation systems for the urban elderly also appear in Table 3. Essentially, although the two-stage least-squares models for transportation of the urban elderly exhibit R^2 levels as high as those for the ordinary least-squares models presented in Table 2, the statistical significance of the demand elasticities is decidedly inferior to that in the ordinary least-squares models.

Both simultaneous-equation models presented show insignificant reservation times and population elasticities; their comparable ordinary least-squares equations in Table 2 show a significant and important population elasticity and mixed results for the reservation-times variable.

The inferior performance of the two-stage least-squares model may be due to the lack of proper specification of the supply function. In fact, the supply function estimates in Table 3 leave a lot to be desired; they show insignificant frequencies of service and population densities. Part of the deficiency in proper specification is, of course, due to the lack of data on costs. Cost data are unavailable for most systems, especially for those funded by monies from HEW.

COMPARISON OF DEMAND ELASTICITIES

As a reference for the comparison of the reasonableness of the elasticities estimated by means of the direct-demand models, Tables 4 and 5 contrast the elasticity estimates from the previous tables with those estimated by other investigators.

The rural transportation models estimated in this study are summarized in Table 4. From the viewpoint of forecasting accuracy, the ordinary least-squares demand models that have supply elements appear superior; evidence is provided by the higher R^2. The two-stage least-squares models are a close second in terms of the R^2 criterion of goodness of fit. In terms of the reasonableness of the demand elasticities, Table 4 shows all the demand elasticities to be reasonable and within the ranges estimated in previous studies (5) for the rural population in general. However, the two-stage least-squares model, which provides unbiased estimates of elasticities, appears to be superior to the ordinary least-squares models in this respect.

The transportation models for the urban elderly are summarized in Table 5. This table shows that

Table 4. Comparison of demand elasticities for the rural elderly.

	Table 1				Table 3		
	Ordinary Least Squares		Reduced Form		Two-Stage Least Squares		
Variable	Equation 2	Equation 4	Equation 3	Equation 5	Model 1	Model 2	Burkhardt and Lago (5)
$ELDPOP_i$	0.17	NA	0.59	NA	0.22	NA	0.3 to 0.5
$ELDPOOR_i$	NA	0.12	NA	0.48	NA	0.20	NA
$ADBUSMILES_i$	0.79	0.80	NA	NA	0.70	0.63	0.84 to 1.09
$FARES_i$	NA	NA	NA	NA	NA	NA	−0.13 to −0.60
$(FR_i) \times (FREQ_i)$	0.09	0.08	0.19	0.17	0.10	0.10	0.50 to 0.60
$(DR_i) \times RESTIME_i)$[a]	−0.11	−0.11	−0.06	−0.07	−0.10	−0.10	−0.27 to −0.50
$COMP_i$	−0.16	−0.13	−0.24	−0.15	−0.38	−0.31	−0.12 to −0.29
$NUTR_i$	0.29	0.28	0.47	0.46	0.71	0.75	NA

Note: NA = elasticity estimate not available from the relevant demand equation.
[a]The elasticity of $RESTIME_i$ is identical to the elasticity of $1/RESTIME_i$ but has changed signs.

Table 5. Comparison of demand elasticities for the urban elderly.

	Table 2				Table 3		Other Studies		
	Ordinary Least Squares		Reduced Form		Two-Stage Least Squares				
Variable	Equation 1	Equation 3	Equation 2	Equation 4	Model 1	Model 2	Kraft and Domencich (13)	Nelson (6)	Schmenner (14)
log $ELDPOP_i$	0.10	NA	0.82	NA	0.04	NA	NA	1.10	0.78 to 1.24
log $ELDPOOR_i$	NA	0.08	NA	0.77	NA	0.04	NA		
log $ADBUSMILES_i$	0.94	0.95	NA	NA	1.01	1.01	NA	0.92 to 1.35	NA
log $FARES_i$	−0.07	−0.07	−0.10	−0.10	−0.07	−0.07	−0.09 to −0.33	−0.67 to −0.81	−0.80 to −0.89
$FREQ_i$	0.17	0.17	0.29	0.30	0.16	0.16	0.30 to 0.71	NA	0.08 to 0.29
$RESTIME_i$[a]	−0.04	−0.03	−0.26	−0.26	−0.02	−0.02	−0.30 to −0.71	NA	NA
$COMP_i$	−0.22	−0.21	−0.48	−0.44	−0.45	−0.45	NA	NA	NA

Note: Fare elasticities estimated in other studies include −0.20 estimated by Warner (16), −0.375 by Lisco (17), −0.11 to −0.68 by Caruolo (1), and −0.30 by Hendrickson and Sheffi (4).
[a]The elasticity of $RESTIME_i$ is identical to $1/RESTIME_i$ but has a change in sign.

the ordinary least-squares models that have supply elements outperform the two-stage least-squares models in terms of R^2, statistical significance, and reasonableness of the elasticity estimates. The reduced-form elasticities are very sensible, but their R^2 values are lower than those for the ordinary least-squares equations, which are the preferred predictive models in this case in spite of their estimation bias. Contrasting these demand elasticities with those of other studies in Table 5, the elderly demand elasticities appear to be slightly underestimated considering that the elderly elasticities should have exceeded the general population elasticities, given the off-peak travel characteristics of the elderly.

CONCLUSIONS

The direct aggregate demand functions for transportation of the elderly presented in this paper show high R^2s and demand elasticities within the ranges estimated by previous investigators. The functions have been estimated from a national data base that includes observations from most of the states. We conclude that they are ready to be used in a variety of planning and design scenarios in both rural and urban settings.

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Cost and Productivity of Transportation for the Elderly and Handicapped: A Comparison of Alternative Provision Systems

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This paper reports on one part of a comprehensive study of 56 specialized transportation providers throughout the United States. Cost and productivity data for three different classes of providers (social service agencies, private contractors, and transit authorities) are presented. Such data were examined for their policy implications for systems currently in operation and proposed coordination and brokerage efforts. A distinction was made between "perceived" costs (items in the budget that require a monetary outlay) and "actual" costs (a more comprehensive account of the required resources for service provision). Such distinction helped explain seemingly irrational choices made by the providers studied and assisted in the determination of an "average" transportation budget for specialized services by major cost items. A comparison of the unit costs experienced by different providers revealed some uniformities: (a) the systems that have the highest productivities operate in dense areas and achieve a mix of group subscription and individual demand-responsive trips, (b) the separation of ambulatory from nonambulatory clients can lead to substantial economies, (c) it is not as clear that contractual agreements offer lower costs when hidden costs are accounted for, and (d) social service agencies are becoming increasingly more expert in the provision of transportation and in many cases have lowered their costs over time to a competitive level. On the basis of these findings, present and planned systems should stress the integration of group and individual trips and the separation of clients by level of service required in order to maximize efficiency.

It is difficult to analyze and evaluate the cost and productivity of transportation systems for the elderly and the handicapped (E&H) because the figures made available by the providers themselves are often incomplete, inaccurate, and scarcely reliable. Existing project reports, each referring to a specific geographic area and period of time, and each employing its own methodology in the definition of costs, do not allow for very meaningful comparisons of alternative provision systems from an economic viewpoint.

At the same time several policy hypotheses have been formulated on the basis of the results of local experiences. Among them are the alleged economic advantage of provision through contractual agreement over direct social service agency (SSA) provision, the opportunity for the heavier involvement of transit authorities in E&H transportation, and the desirability of mixing different client and trip types. Although supported by individual studies (and sometimes contradicted by others), many of these hypotheses have not been tested against comparable or consistent data sets.

In 1978-1979 the University of Texas at Austin undertook a national study of the cost and effectiveness of alternative E&H transportation systems sponsored by the U.S. Department of Transportation. The study attempted to provide a detailed nationwide data base whose cost and productivity measures were developed by using a consistent methodology and comparable terminology. [All data presented here appear in more detailed form in that project's final report (1).]

STUDY BACKGROUND

The purposes of the University of Texas study were manifold; they included

1. To look at the cost and productivity of different alternatives in order to isolate the characteristics of the most productive and more economic systems,
2. To examine the impact of different forms of assistance (for example, capital grants for purchase of equipment as opposed to operating subsidies) on the behavior of the recipients at the local level,
3. To develop a data base that would provide reference figures for a manual (2) addressed to the planning and evaluation needs of local E&H transportation providers, and
4. To formulate policy suggestions based on the observed uniformities and the relative advantages of particular provision alternatives.

Fifty-six providers were surveyed and were grouped into three major classes and further divided as shown below:

1. Social service agencies (17): 7 national and regional, 5 in urban setting, and 5 in rural setting;
2. Contract providers (28): 10 urban, not lift-equipped; 6 urban, lift-equipped; and 12 rural, lift-equipped; and
3. Transit-managed systems (11): urban, at least partly lift-equipped.

Two different definitions of cost were elaborated