Transportation (2006) 33: 311–328
DOI 10.1007/s11116-005-0328-7

Household mobility tool ownership: modeling interactions between cars and season tickets

DARREN M. SCOTT[1,]* & KAY W. AXHAUSEN[2]
[1]*Center for Spatial Analysis, School of Geography and Earth Sciences, McMaster University, 1280 Main St. West, Hamilton, Ontario, L8S 4K1 Canada;* [2]*Institute for Transport Planning and Systems (IVT), ETH Zurich, CH-8093 Zurich, Switzerland*
*(*Author for correspondence, E-mail: scottdm@mcmaster.ca)*

Key words: bivariate ordered probit model, car ownership, mobility tool, season ticket ownership, stated response survey, transit

Abstract. This paper moves beyond traditional models of car ownership in that we propose a framework for modeling household-level decisions to acquire specific types and numbers of mobility tools to fulfill the mobility needs of household members. The framework is applied to a data set collected during the winter and spring of 2000/2001 in the German city Karlsruhe via an interactive web-based stated response survey in which respondents could optimize their household mobility tool sets through on-line feedback concerning the estimated costs of the sets. In our analysis, bivariate ordered probit models are estimated for three combinations of mobility tools: season tickets (i.e., transit passes) and cars, season tickets and small cars and season tickets and large cars. In all instances, strong substitution effects are found – that is, as the number of season tickets increases, the number of cars decreases. This finding underscores the need to move beyond simple models of car ownership to comprehensive models of mobility tool ownership. As demonstrated by our research, failure to do so is likely to lead to biased results.

1. An overlooked dependency: cars and season tickets

Individuals and households fix the perceived short-run marginal costs of their kilometers traveled by acquiring mobility tools – that is, vehicles (e.g., sport utility vehicles, cars, minivans) and season and discount tickets for public transit (i.e., transit passes). Although the exact relationship between real and perceived short-run costs has not been a subject of detailed study, a general professional consensus would be that car drivers consider only those direct out of pocket costs, which they have to bear themselves at the point of use, while season ticket owners consider public transport free at the point of use and discount ticket owners discount the fare at the rate to which they are entitled with the ticket – for example, 50% for interurban rail as the owner of a Swiss Halbtaxabonnement. The mixture of available tools will therefore influence heavily the mode choice of the traveler. Not only this, but a season ticket can serve as an alternative to an extra car when household members have chosen their work places given their home location.

Still, with the exception of earlier work by Axhausen and colleagues (see Simma & Axhausen 2001, 2003; Axhausen et al. 2004), this interaction is generally being ignored by modelers, and also by policy makers (see de Jong et al. 2004 for a comprehensive review of recent car ownership modeling). This situation is not justifiable in a European or Japanese context where season tickets are widely available, nor is it justifiable in a North American context where monthly transit passes are available. The data required for modeling season ticket and car ownership jointly can be obtained easily as part of a travel diary survey through one or more additional questions concerning season ticket ownership. Ideally, such questions would elicit information on the temporal and spatial coverage and the cost of season tickets owned.

Monthly season tickets (i.e., transit passes) are widely available in Canada and the United States, but they are priced differently than in German-speaking European countries. An analysis of data obtained for 2003 from the American Public Transit Association, for example, showed that such tickets are sold in Canada and the United States at an average multiple of 32 times the price of a single ticket (APTA 2003), while in a sample of 45 transit authorities in German-speaking countries the multiple was 24 times. While the average is higher in Canada and the United States, so is the range, which spans values from 8 to 85 times the single ticket price, while the European sample only ranges from 14 to 34 times the single price.

A possible reason for not addressing the issue of joint ownership of mobility tools is the difficulty of modeling such joint choices satisfactorily, in particular if one is interested in capturing interactions or tradeoffs between mobility tools of different types (e.g., cars and season tickets). Models capable of capturing multivariate ownership choice have been available for quite some time. Examples include nested logit, cross-nested logit, multivariate probit and structural equation models. With the exception of structural equation models, however, these models do not capture explicitly interactions between dependent variables. Further, the structural equation model is not well suited to outcomes that are discrete in nature. The joint ownership of mobility tools at the household level necessarily implies that the dependent variables are both discrete and ordinal – that is, one is interested in the number of cars and the number of season tickets owned by households while accounting for tradeoffs between the tool types.

The purpose of this paper is to show how the bivariate ordered probit model can be used to capture the dependencies between the mobility tool choices at the household level more fully by allowing not only the modeling of the presence of a tool, but of the exact number of each type. The following section describes the stated response (SR) data set to which the approach is applied. The main part of the paper consists of two sections describing the econometric approach and the empirical analysis. The concluding section discusses the results and their implications for modeling and policy practice.

2. Description of the survey

2.1. *Project context*

The data set analyzed was collected as part of the Mobiplan project, which developed an internet-based transport advisory tool for potential movers (see PTV AG et al. 2000; Kreitz et al. 2001; Zimmermann & Fell 2001) on the basis of an improved understanding of moving behavior and the impact of the move on travel (see Zimmermann & Fell 2001 for the survey work undertaken). The project focused its attention on recently moved households, which were recruited into a two-wave panel spanning approximately the first 6 months after the move. The cities of Karlsruhe and Halle and the surrounding Kreise[1] provided addresses of households, which had moved into their areas, from their population registers.[2] In an initial screening, households were removed if they had relocated from outside the two study areas (Karlsruhe and Halle and their environs, defined as the service area of the local Verkehrsverbund[3] in Karlsruhe and the surrounding Kreise in the case of Halle), as the project wanted to see how the travel behavior adjusted to the new location within the existing environment of the household (see Downs & Stea 1977 for the impact of existing mental maps). Householders born before 1930 were omitted to exclude the special group of retirees moving into their (possibly) last accommodation. The sample collected matched the known characteristics of movers in the study areas.

2.2. *The mobility tool ownership stated-response exercise*

The Mobiplan advisory tool (Kreitz et al. 2001) is implemented as a web-based service. To allow customization, it includes a basic survey of the socio-demographics of a person and of his/her mobility preferences. In the overall context of the project, it was an obvious choice to use this platform for further internet-based surveys. One of these was a stated-response (SR) survey of the preferences for the composition of the household's mobility tools. The logic of the long-term time horizons of these choices implies that the residents can focus only on a small number of core variables, as they are themselves unable to assess the costs and travel times of all their future travel. Still, they know their workplace, they can identify the nearest local shopping area and they have an idea of their leisure preferences and the associated locations (i.e., sporting grounds, clubs, etc.). They also know about their need for work-related travel and their preferences with regards to travel for their main holidays.

While work-related travel is becoming less important in its share of trips and kilometers traveled, it is still the major time commitment of a person. Thus, the quality of the connection between home and work is important (see Stutzer & Frey 2003). The same applies, but with less force, to the connections with daily and weekly shopping. Leisure, with the exception of some firm commitments (i.e., clubs, church, etc.), is too disperse for a household for detailed advance assessment.

Given this information, the household has to decide on the level of speed, the travel times and marginal costs it wishes to enjoy. The variables of the SR experiment were selected in line with this argument (see Table 1). This set, arrived at independently, is similar in spirit to that used by Eliasson in his dissertation on housing location and travel choices (see Eliasson & Mattson 2000) and Boarnet and Crane (2001a, b) in their work on the impact of urban form on travel behavior. The types of housing and the specific space per person match the local conditions. The size of the accommodation was customized for each respondent based on the number of members in his/her household plus a share for the common areas of a house or flat. Each of the respondents answered eight out of 72 situations of an orthogonal factorial design (König 2001).

The experiment was not formulated as a traditional stated-choice exercise, but as a more open stated-response query. While the housing situation and the travel times to work and local shopping were given, the respondent had to compose the set of mobility tools. Specifically, the respondent had to choose for each adult household member, with a firm commitment to daily travel (i.e., work and study), the type of car (i.e., none, subcompact, compact, family, luxury, people mover) and the type of season ticket (i.e., none, monthly, annual). The total cost of each set was estimated using rough assumptions about the average cost of each vehicle type and the average amount of travel given the location (König 2001). The respondent could then refine the selection until it matched his/her preferences. This iterative element is unusual and only possible in a computer-supported exercise.

The survey was conducted during the winter and spring of 2000/2001 at the Institut für Soziologie of the Universität Karlsruhe. The sample was recruited to match certain age and household-size criteria. In particular, the bulk of the respondents should be economically active and in a situation

Table 1. Variables of the SR experiment and their attribute levels.

Variable	Attribute levels							
Location of residence	CBD with balcony	Urban with balcony		Suburban with garden			Rural with garden	
Type of accommodation	Flat	Terrace	Flat	Detached	Terrace	Flat	Detached	Terrace
Size of accommodation								
Common area (m^2)	30	30	30	50	40	30	60	50
Per person (m^2)	20	20	20	20	20	20	25	25
Mortgage per month (DM)	$m^2 \times 15$	$m^2 \times 14$	$m^2 \times 13$	$m^2 \times 13$	$m^2 \times 12$	$m^2 \times 11$	$m^2 \times 10$	$m^2 \times 9$
Rent (DM)	$m^2 \times 15$	$m^2 \times 14$	$m^2 \times 13$	$m^2 \times 13$	$m^2 \times 12$	$m^2 \times 11$	$m^2 \times 10$	$m^2 \times 9$
Car travel time to work (min)	10, 20, 30	10, 20, 30		20, 30, 40			30, 45, 60	
Car travel time to shopping (min)	5, 10	5, 10		10, 20			15, 30	
Transit travel time to work (min)	10, 20, 30	10, 20, 30		20, 30, 40			30, 45, 60	
Transit travel time to shopping (min)	5, 10	5, 10		15, 30			30, 45	
Headway at local stop (min)	5, 10	10, 15		15, 30			30, 60	
Distance to local stop (m)	100, 200, 300	100, 200, 300		100, 300, 500			300, 500	

Source: Axhausen et al. (2004), Table 2.

Table 2. Independent variables used in the empirical analysis.

Variable	Definition
Household characteristics	
Two members with daily commitments	1 if household contains two members who must travel daily for work and/or study; 0 otherwise
Three members with daily commitments	1 if household contains three members who must travel daily for work and/or study; 0 otherwise
Four members with daily commitments	1 if household contains four members who must travel daily for work and/or study; 0 otherwise
Household income	Monthly household income in DM $\times 10^{-3}$
Housing costs	Monthly housing costs in DM $\times 10^{-3}$
Household income $\times$ housing costs	Household income interacted with housing costs
Residential location characteristics	
Suburb	1 if residence is located in the suburbs; 0 otherwise
Rural	1 if residence is located in the countryside; 0 otherwise
Travel time difference to work	Travel time to work by car minus travel time to work by public transit in minutes $\times 10^{-1}$
Travel time difference to shop	Travel time to shop by car minus travel time to shop by public transit in minutes $\times 10^{-1}$
Distance to nearest public transit stop	Distance to nearest public transit stop in kilometers
Headway at nearest public transit stop	Headway at nearest public transit stop in minutes $\times 10^{-1}$

where the choice situation described is relevant to them. In addition, there was to be an equal share of men and women. Sixty respondents participated as part of a larger evaluation of the Mobiplan advisory tool, while a further 106 undertook only this SR experiment and two further stated-choice surveys under interviewer supervision.

3. Econometric approach

3.1. *Overview*

Household ownership levels of cars and season tickets are modeled using both univariate and bivariate ordered probit models. The latter model is an extension of the former, which was developed by McKelvey and Zavoina (1975) to capture the discrete and ordinal nature of some decisions. In addition to this strength, the bivariate ordered probit model, like the trivariate ordered probit model developed by Scott and Kanaroglou (2002), captures interactions or tradeoffs between decisions. In this paper, the tradeoff is between the number of cars and the number of season tickets to own at the household level.

3.2. *Bivariate ordered probit model*

In the following presentation of the model structure, for each household h, j represents the number of cars ($j = 0, 1, \ldots, J$) and k represents the number of season tickets ($k = 0, 1, \ldots, K$). The equation system is written as:

$$\begin{aligned} y_{1h}^* &= \beta_1 x_{1h} + \varepsilon_{1h},\ y_{1h} = j \quad \text{if } \mu_{1,j} < y_{1h}^* \leq \mu_{1,j+1}, \\ y_{2h}^* &= \beta_2 x_{2h} + \varepsilon_{2h},\ y_{2h} = k \quad \text{if } \mu_{2,k} < y_{2h}^* \leq \mu_{2,k+1}, \end{aligned} \tag{1}$$

where y_{1h}* and y_{2h}* are, respectively, the propensities for household h to own cars and season tickets. The observed number of cars is represented by y_{1h} and the observed number of season tickets is represented by y_{2h}. The xs are vectors of exogenous variables. The βs are corresponding vectors of parameters that are estimated along with the threshold values (i.e., the μs) for each equation. The random error terms ε_{1h} and ε_{2h} are assumed to be distributed identically and independently across households in accordance with the standard normal distribution.

As argued already, a household must compose a set of mobility tools to fulfill its needs based on perceived short-run costs subject to budget constraints. The key to capturing the tradeoff between numbers of cars and season tickets is to correlate the random error terms ε_{1h} and ε_{2h}. For this, a standard normal bivariate distribution function is specified such that:

$$\phi_2(.) = \phi_2\left(\varepsilon_{1h}, \varepsilon_{2h}, \rho_{\varepsilon_1\varepsilon_2}\right). \tag{2}$$

The corresponding cumulative density function is given as:

$$\Phi_2(.) = \Phi_2\left(\varepsilon_{1h}, \varepsilon_{2h}, \rho_{\varepsilon_1\varepsilon_2}\right). \tag{3}$$

The ρ represents the correlation between the random error terms.

From (1) and (3), the joint probability that household h will choose j cars and k season tickets is:

$$\begin{aligned} P_{hjk} = {} & \Phi_2\left[(\mu_{1,j+1} - \beta_1 x_{1h}), (\mu_{2,k+1} - \beta_2 x_{2h}), \rho_{\varepsilon_1\varepsilon_2}\right] \\ & - \Phi_2\left[(\mu_{1,j} - \beta_1 x_{1h}), (\mu_{2,k+1} - \beta_2 x_{2h}), \rho_{\varepsilon_1\varepsilon_2}\right] \\ & - \Phi_2\left[(\mu_{1,j+1} - \beta_1 x_{1h}), (\mu_{2,k} - \beta_2 x_{2h}), \rho_{\varepsilon_1\varepsilon_2}\right] \\ & + \Phi_2\left[(\mu_{1,j} - \beta_1 x_{1h}), (\mu_{2,k} - \beta_2 x_{2h}), \rho_{\varepsilon_1\varepsilon_2}\right]. \end{aligned} \tag{4}$$

The parameters estimated in the bivariate ordered probit model are the $J+K-2$ threshold values ($\mu_{1,0}$, $\mu_{2,0} = -\infty$; $\mu_{1,1}$, $\mu_{2,1} = 0$; $\mu_{1,J+1}$, $\mu_{2,K+1} = +\infty$), the βs and the ρ. The parameters are obtained by maximizing the log-likelihood function:

$$L^* = \sum_{h=1}^{H} \sum_{j=0}^{J} \sum_{k=0}^{K} Z_{hjk} \log P_{hjk}, \tag{5}$$

where

$$Z_{hjk} = \begin{cases} 1 & \text{if household } h \text{ chooses } j \text{ cars and } k \text{ season tickets,} \\ 0 & \text{otherwise.} \end{cases}$$

A program is written in GAUSS™ (Aptech Systems 2002) for this task.

4. Empirical analysis

4.1. *Model specification*

In modeling household mobility tool composition, a distinction was made not only between cars and season tickets, but also between small cars and large cars. Given inherent differences in both purchasing and perceived operating costs, not to mention other characteristics, it is reasonable to assume that households assign different utilities to each type of car. From the analyst's point of view, the weights assigned to factors influencing the decision-making process are both observed and unobserved. Whereas the former are captured by parameter estimates for measured variables such as household income, the latter are accounted for by random error terms for the households. For instance, prestige may be important to higher-income households when choosing between a small car and a large car, such as an SUV. This factor would, in all likelihood, be unobserved by the analyst. To account for such differences in both observed and unobserved factors, models are estimated separately for small and large cars in addition to a model for all cars.

The variables included in the final model specifications are found in Table 2, along with their definitions. These variables are arranged into two groups with the first corresponding to household characteristics. This group includes the number of members with firm commitments to daily travel (i.e., work and/or study), household income and housing costs. The number of members with daily commitments is included in the models by a series of dummy variables. One commitment serves as the reference category. These variables not only capture the importance of daily commitments on mobility tool ownership, but also account for differences in household size. It is hypothesized that a positive relationship exists between the number of household members with daily commitments to travel and the number of cars and the number of season tickets owned. In general, household income is spent on three categories of goods: housing, mobility tools and all other goods. Obviously, as more income is spent on housing, less remains for mobility tools and all other goods. To account for the relationship between income and housing costs and its effect on mobility tool ownership, an interaction term is created by multiplying household income by housing costs. It is hypothesized that the effect of income on car and season ticket ownership differs according to housing costs – that is, with higher housing costs, less income is left for the acquisition of mobility tools meaning that the effect of income will decrease with increasing housing costs.

The second group of variables corresponds to characteristics associated with the residential location of the households. A series of dummy variables describing the location of households within the urban system is included in the models. These dummy variables correspond to the urban core (including CBD), suburbs and urban fringe. The urban core serves as the reference category. A positive relationship is postulated between the number of cars owned and distance from the CBD, as measured by the locational variables. The opposite relationship is postulated for the number of season tickets owned. Distance to the nearest public transit stop, travel time differences to work and to shop and the headway at the nearest public transit stop are also included in final model specifications.

Four models comprise the univariate results. Three models are estimated accounting for interactions between ownership levels of season tickets and cars, season tickets and small cars and season tickets and large cars.

A negative relationship is postulated between the number of season tickets owned and the number of cars owned. Simma and Axhausen (2001) find such a relationship between car availability and season ticket ownership for individuals included in three national surveys – namely, those for Switzerland, Germany and Great Britain. Additionally, we attempted to estimate a trivariate ordered probit model containing season tickets, small cars and large cars. However, due to many potential outcomes containing zero observations (for example, it is unreasonable to expect that a household would own three season tickets, three small cars and two large cars), the model failed to converge.

4.2. *Univariate results*

Table 3 presents the parameter estimates and *t*-statistics for univariate models of household mobility tool ownership. These models represent the best specifications whereby all variables are significant at the 0.10 significance level. Also, the models perform well as indicated by the large values of ρ^2.

As expected, there is a positive relationship between season ticket ownership and the number of household members with firm commitments to daily travel. With respect to the impact of household income interacted with housing costs on season ticket ownership, the effect of income decreases as housing costs increase. This is to be expected as less income is available, in general, to acquire mobility tools. A similar relationship is found with regards to the effect of housing costs on season ticket ownership – that is, the effect of housing costs decreases as household income increases. In this instance, more income is available to acquire mobility tools, thus diminishing the effect of housing costs.

Three residential location characteristics are found to impact season ticket ownership. The effects of two variables, travel time difference to work and travel time difference to shop, depend on the sign of the variables. The reason for this is that these variables are derived by subtracting the travel time by public transit from the travel time by car. Thus, if it takes less time to travel by car either to work or to shop, as indicated by a negative value for the variable, then the effect on season ticket ownership is negative. In turn, the effect is positive if travel by public transit takes less time. This finding suggests that individuals not only consider the monetary costs associated with alternative modes, but also their temporal costs. Also, the values of the parameter estimates suggest that the impact will be greater for travel time differences to shop than to work. Finally, distance to the nearest public transit stop has a negative impact on household season ticket ownership. This is to be expected as greater distance necessarily adds to the duration of a trip.

Table 3. Estimation results for univariate ordered probit models of household mobility tool ownership.

Variable	Number of season tickets		Number of cars		Number of small cars		Number of large cars	
	Coefficient	*t*-statistics	Coefficient	*t*-statistics	Coefficient	*t*-statistics	Coefficient	*t*-statistics
Constant term	−0.088	−0.205	−2.540	−6.067	−2.108	−4.874	−3.706	−14.718
Household characteristics								
Two members with daily commitments	0.800	8.050	0.622	6.362	0.808	8.443	−0.392	−3.986
Three members with daily commitments	1.290	8.804	1.580	10.365	1.620	10.859		
Four members with daily commitments	2.044	9.591	1.523	6.361	1.338	5.534		
Household income	0.200	2.129	0.441	4.581	0.405	4.099	0.314	9.796
Housing costs	1.311	3.500	1.713	4.735	1.534	4.090	1.345	8.746
Household income × housing costs	−0.347	−4.401	−0.286	−3.598	−0.416	−5.033		
Residential location characteristics								
Suburb			0.745	8.791	0.602	6.842	0.350	3.027
Rural			1.270	12.541	1.103	11.327	0.403	3.200
Travel time difference to work (car minus public transit)	0.169	6.500	−0.134	−4.892	−0.128	−4.670		
Travel time difference to shop (car minus public transit)	0.578	7.044						
Distance to nearest public transit stop	−0.465	−1.9255						
Threshold values								
One and two	1.426	24.293	1.971	26.514	1.841	24.942	2.098	13.590
Two and three	3.080	24.659	3.531	22.733	3.618	17.249		
Summary statistics								
n		1034		1034		1034		1034
$L^*(0)$		−1433		−1433		−1433		−1136
$L^*(\beta)$		−1018		−892		−871		−442
ρ^2		0.29		0.38		0.39		0.61

Like the model for season ticket ownership, the parameters estimated for car ownership are also as expected. With respect to housing characteristics, there is a positive relationship between the number of household members with daily commitments to travel and car ownership. However, unlike season ticket ownership, the effect is maximized with three members, not four. A likely explanation for this is that cars are simply more expensive than season tickets. Given a household income, a percentage will be allocated to mobility tool acquisition. In the case of three members, it may be possible to purchase and operate more cars than in the case of four members. The reason for this is that the fixed income must be divided among four mobility tools, not merely three. Thus, it may be necessary to purchase season tickets over cars in order to meet budget constraints. Only an increase in household income or a decrease in housing costs will alter this situation. As shown in Table 3, these variables impact household car ownership levels in the same way that they impact ownership of season tickets.

With respect to residential location characteristics, residing in areas outside the urban core has a positive impact on car ownership with the impact being greater for rural areas than for suburbs where public transit is available, but less frequently. Finally, the travel time difference to work also has a significant impact on car ownership. The greater this difference favoring the car (the value of the variable is negative), the more positive the impact.

The remaining models shown in Table 3 distinguish between small and large car ownership levels. The effects of household and residential location characteristics on the model for small cars are identical in sign and similar in magnitude to those just discussed for all cars. Whereas the model calibrated for small cars is similar to that for all cars, the same cannot be said for the model shown in Table 3 for large cars. With respect to household characteristics, only one variable measuring the effect of daily commitments to travel on large car ownership is significant. Moreover, the effect of two members with such commitments is negative. This finding suggests that the propensity to own large cars is greater when only one member needs a mobility tool for daily travel. In this case, household income allocated to mobility tools does not have to be allocated between two members. The finding also suggests that a large car may become a necessity for larger households in which three or four members have daily commitments. This is likely the case when households have children in school – that is, a large car is required as a people mover. It may also be the case that the need for at least one large car is greater for large households than for smaller households for non-commitment purposes such as leisure activities. Again, this is likely the case in households with children. As mentioned, the household commitment variable is also a surrogate for household size. Finally, unlike the preceding models, the interaction between household income and housing costs is insignificant. Instead, with both increasing income and increasing housing costs, the propensity to own large cars increases. The first effect suggests that higher income households prefer larger, more expensive cars such as Mercedes or BMW sedans. In this case, such cars may be viewed as a status symbol. At the same time, the second effect suggests that households living in more expensive houses prefer larger cars. Again, this effect suggests that a large car is a status symbol – that is, people residing in an expensive house will also have an expensive car. In many respects, although there is not a significant interaction effect, the effect of income and housing costs on large car ownership parallel one another. More income leads to a more expensive house, most likely in the suburbs or countryside, which, in turn, leads to a more expensive car. Evidence suggesting that such cars are preferred in such residential environments is also given in the model by the positive values for suburb and rural.

4.3. *Bivariate results*

A fundamental shortcoming of the models presented in Table 3 is that ownership levels are considered separately for each type of mobility tool. Obviously, such a decision-making process is a creation of the analyst, not reflecting that which actually occurs. In reality, household members, given budget constraints, must make tradeoffs when deciding upon the types and numbers of mobility tools to acquire to meet their travel needs. This implies a joint or simultaneous decision-making process. The models presented in Table 4 reflect such a process with tradeoffs between mobility tools being captured by the correlation coefficients. These models are the best models estimated using household and residential location characteristics as explanatory variables. All models perform well as indicated by the high values of ρ^2.

The first model considers the tradeoff between number of season tickets and number of cars. The large negative value of the correlation coefficient (i.e., −0.57) suggests that there is a strong substitution effect – that is, as the number of season tickets increases, the number of cars decreases. This finding is as hypothesized, suggesting a strong preference for one type of mobility tool over the other to meet household needs for daily travel. For both season tickets and cars, the parameter estimates for the variables corresponding to the number of members with commitments for daily travel are also as hypothesized. As the number of such members increase, their impact on the propensities to own season tickets and cars also increases. This reflects the fact that additional mobility tools are simply required to meet household needs for daily travel. Household income is significant for both season tickets

Table 4. Estimation results for bivariate ordered probit models of household mobility tool ownership.

Variable	Season tickets and cars		Season tickets and small cars		Season tickets and large cars	
	Coefficient	*t*-statistics	Coefficient	*t*-statistics	Coefficient	*t*-statistics
Number of season tickets						
Constant term	1.312	10.872	1.311	9.501	1.329	10.283
Household characteristics						
Two members with daily commitments	0.769	9.723	0.776	9.328	0.772	9.790
Three members with daily commitments	1.211	9.132	1.222	9.205	1.203	9.279
Four members with daily commitments	2.126	11.157	2.122	11.171	2.147	11.593
Household income	−0.171	−7.179	−0.175	−6.649	−0.175	−6.870
Residential location characteristics						
Travel time difference to work (car minus public transit)	0.166	6.029	0.168	6.132	0.164	6.166
Travel time difference to shop (car minus public transit)	0.567	7.780	0.583	7.524	0.565	7.315
Distance to nearest public transit stop	−0.509	−2.406	−0.475	−1.940	−0.541	−2.228
Threshold values						
One and two	1.402	24.797	1.396	24.254	1.415	24.415
Two and three	3.069	27.982	3.041	26.981	3.023	27.759
Number of cars/small cars/large cars						
Constant term	−0.778	−6.616	−0.379	−2.812	−3.487	−20.085
Household characteristics						
Two members with daily commitments	0.718	8.803	0.737	8.719	−0.392	−3.929
Three members with daily commitments	1.783	12.749	1.474	10.443		
Four members with daily commitments	2.059	10.700	1.390	7.577		
Household income	0.140	5.848	−0.049	−2.053	0.302	11.139
Housing costs					1.220	8.652
Residential location characteristics						
Suburb	0.647	8.029	0.545	6.484	0.315	2.950
Rural	1.242	12.649	1.036	10.428	0.405	3.308
Travel time difference to work (car minus public transit)	−0.131	−4.693	−0.123	−4.438		
Threshold values						
One and two	1.947	27.449	1.806	20.383	2.157	12.715
Two and three	3.568	28.397	3.623	20.053		
Correlation coefficient	−0.577	−20.101	−0.390	−9.447	−0.360	−7.470
Summary statistics						
n		1034		1034		1034
$L^*(0)$		−2867		−2867		−2569
$L^*(\beta)$		−1816		−1865		−1467
ρ^2		0.37		0.35		0.43

and cars, but has opposite signs. This finding suggests that with increasing income, the gap in preference for cars over season tickets widens.

Three residential location characteristics are significant for season ticket ownership. Both travel time difference to work and to shop have positive signs. Their effects, however, depend on signed values of the variables. If the travel time differences favor travel by public transit, then the effects are positive. Likewise, the effects are negative if the travel time differences favor travel by cars. The negative parameter estimate for distance to nearest public transit stop indicates that individuals are sensitive to additional travel that must be incurred by foot to reach public transit.

With respect to cars, the propensity to own them is directly related to residential location. In fact, the farther a household is located from the urban core, the greater the likelihood that it will own one or more cars. Obviously, this reflects, in part, poor public transit service. Also, the greater the travel time difference to work favoring the car, the greater its positive impact on household car ownership levels.

The remaining two models in Table 4 distinguish between car type – that is, one model considers the tradeoff between the number of season tickets and the number of small cars and the other, the number of season tickets and the number of large cars. In both models, there is a negative correlation between level of season ticket ownership and level of car ownership, suggesting a substitution effect. Furthermore, a comparison of the magnitudes of the correlation coefficients indicates little difference in the tradeoff between number of season tickets and number of large cars and the tradeoff between number of season tickets and number of small cars. However, the magnitudes of both coefficients are far less than that for the first model – 0.18 less in the case of small cars and 0.21 less in the case of large cars. Together, these findings suggest that some households acquire a mixture of car types. Individually, ownership levels of small cars and large cars are more similar to ownership levels of season tickets than when they are combined.

The results in both models concerning number of season tickets parallel the results discussed above for the first model. The same cannot be said with respect to number of small cars and number of large cars. In the case of the former, the propensity to own small cars varies with the number of household members with commitments to daily travel. Unlike the model for all cars, the effect of household income is negative suggesting that at higher income levels, large cars may be preferred over small ones. The interpretation of the residential location characteristics for small car ownership levels is the same as that for all cars. By comparison, the bivariate model results for large cars parallel those discussed in the univariate case and will not be repeated here.

5. Conclusion

This paper contributes significantly to the literature on mobility tool ownership. As argued at the outset, with few exceptions, modelers have ignored tradeoffs that household members make when choosing both types and numbers of mobility tools to meet their daily needs for travel. In particular, there appears to be a paucity of information on season ticket ownership. The same cannot be said, however, of car ownership. In fact, car ownership is an integral component of many activity-based models of urban travel demand that are being developed currently (see, for example, Miller et al. 2004 for a discussion of the importance of car ownership to such models). The findings reported in this paper, however, suggest that season ticket ownership can no longer be ignored. At the very least, the findings suggest that car ownership models may produce misleading results as they do not consider possible interactions between cars and season tickets. While some may argue that this is of little concern in North American cities, it remains to be verified empirically. It must be remembered that public transit systems in North America also offer a form of season ticket – the monthly transit pass.

Not only is there a tradeoff between number of season tickets and number of cars, the findings reported in this paper confirm that the strength of the tradeoff varies according to the types of cars considered. When all cars are pooled, the tradeoff with season tickets is very strong suggesting a strong substitution effect – that is, households exhibit a strong preference for either season tickets or cars. However, in the unpooled models, the strength of the interaction is diminished, but by no means, less important. In fact, the differences in the correlation coefficients suggest that households may acquire some mixture of all tools to meet their mobility needs. In fact, an attempt was made to model the mixture of all tools using the trivariate ordered probit model developed by Scott and Kanaroglou (2002). However, the attempt failed as too many alternatives were associated with zero observations (for example, the alternative consisting of three season tickets, three small cars and two large cars).

The results of this study and those reported in Axhausen et al. (2004) demonstrate the usefulness of SR surveys as alternatives to revealed preference surveys as means for collecting data for use in calibrating predictive models. Although they were not shown, univariate and bivariate models containing personal characteristics of the respondents were also estimated. While some characteristics were significant (e.g., age, experience with specific tools), no inherent bias was found with respect to household and residential location characteristics. Furthermore, the effects of the personal characteristics on the explanatory power of the models were minimal.

A final contribution of this study is that it introduces the bivariate ordered probit model to the field of travel behavior analysis as a powerful modeling tool. Specifically, it can be applied to any situation involving two interrelated decisions in which the alternatives are discrete and ordinal.

Acknowledgements

The Mobiplan survey work was funded by the German Ministry of Research and Technology. This and the contributions made by the partners of the Mobiplan project (PTV AG, Karlsruhe, Institut für Stadtbauwesen, RWTH Aachen, Institut für Soziologie, Universität Karlsruhe) are gratefully acknowledged.

Notes

1. The German federal states, Länder, are organized into municipalities, which cover their areas exhaustively. All but the largest of them (i.e., the major cities) are grouped into Kreise, which take on various administrative tasks, some delegated from the municipalities and some delegated from the Land.
2. All moving households have to register with their local population register within a short number of weeks. Non-compliance can be fined. The register serves various functions, such as the electoral roll, as the draft register, as the basis for tax lists, etc.
3. Verkehrsverbünde organize the local and regional public transport provision in most German agglomerations. Their legal status and internal organization differs from region to region, which make generalizations difficult.

References

APTA (2003) *2003 Transit Fare Summary*. Washington, DC: APTA (American Public Transit Association).

Aptech Systems (2002) *GAUSS 5.0*^{TM}. Maple Valley, WA: Aptech Systems.

Axhausen KW, König A, Scott DM & Jürgens C (2004) Locations, commitments and activity spaces. In, Schreckenberg M & Selten R (eds) *Human Behaviour and Traffic Networks* (pp. 205–230). Berlin: Springer.

Boarnet MG & Crane R (2001a) The influence of land use on travel behavior: specification and estimation strategies. *Transportation Research Part A: Policy and Practice* 35: 823–846.

Boarnet MG & Crane R (2001b) *Travel by Design: The Influence of Urban Form on Travel*. Oxford: Oxford University Press.

de Jong G, Fox J, Daly A, Peiters M & Smitt R (2004) Comparison of car ownership models. *Transport Reviews* 24: 379–408.

Downs RM & Stea D (1977) *Maps in Mind*. New York: Harper and Row.

Eliasson J & Mattson L-G (2000) A model for integrated analysis of household location and travel choices. *Transportation Research Part A: Policy and Practice* 34: 375–394.

König A (2001) Eine interaktive Stated-Preference Befragung zur Wohnstandortwahl, *Arbeitsberichte Verkehrs- und Raumplanung*, Vol. 81. ETH Zürich, Zürich: Institut für Verkehrsplanung, Transporttechnik, Strassen- und Eisenbahnbau.

Kreitz M, Axhausen KW, Friedrich M & Beckmann KJ (2001) Mobiplan: an internet-based mobility advisor, *Arbeitsberichte Verkehrs- und Raumplanung*, Vol. 94. ETH Zürich, Zürich: Institut für Verkehrsplanung, Transporttechnik, Strassen- und Eisenbahnbau.

McKelvey RD & Zavoina W (1975) A statistical model for the analysis of ordinal level dependent variables. *Journal of Mathematical Sociology* 4: 103–120.

Miller EJ, Hunt JD, Abraham JE & Salvini PA (2004) Microsimulating urban systems. *Computers, Environment and Urban Systems* 28: 9–44.

PTV AG, Fell B, Schönfelder S & Axhausen KW (2000) *Mobidrive questionaires, Arbeitsberichte Verkehrs- und Raumplanung*, Vol. 52. ETH Zürich, Zürich: Institut für Verkehrsplanung, Transporttechnik, Strassen- und Eisenbahnbau.

Scott DM & Kanaroglou PS (2002) An activity-episode generation model that captures interactions between household heads: development and empirical analysis. *Transportation Research Part B: Methodological* 36: 875–896.

Simma A & Axhausen KW (2001) Structures of commitment and mode use: a comparison of Switzerland, Germany and Great Britain. *Transport Policy* 8: 279–288.

Simma A & Axhausen KW (2003) Commitments and modal usage: analysis of German and Dutch Panels. *Transportation Research Record* 1854: 22–31.

Stutzer A & Frey BS (2003) Stress that doesn't pay: the commuting paradox. Institute for Empirical Research in Economics Working Paper, 151, University of Zurich, Zürich.

Zimmermann A & Fell B (2001) Mobiplan: Zweistufige Panelbefragung von umgezogenen Haushalten. Rekrutierungskonzept, Befragungsinhalte und Betreuung. *Stadt Region Land* 71: 107–114.

About the authors

Dr. Darren M. Scott is an Assistant Professor of Geography at McMaster University. His current research centers on inter-agent decision making with regards to activity-travel behavior, and on issues concerning aggregation in activity-based travel demand models, most notably the treatment of space and the classification of activities.

Dr. Kay W. Axhausen is a Full Professor of transport planning at ETH Zürich (Swiss Federal Institute of Technology). The focus of his research is the measurement and modeling of travel behavior and long-term mobility choices.