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Modeling car-sharing membership as a mobility tool: A multivariate Probit approach with latent variables

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Abstract

Individual travel behavior is to a large extent shaped by the respective portfolio of available mobility tools such as cars, season-tickets or a car-sharing membership. However, the choices of different mobility tools are interdependent and are also affected by individual attitudes. This paper presents an approach to jointly model the choice of four different mobility tools - including car-sharing. Using data from the Swiss transportation micro census of 2005 and 2010, it is shown that car-sharing is used as a supplement to a public transportation-oriented lifestyle, but is also used by car owners. The results further indicate that personal attitudes have a substantial effect on the choice of mobility tools and should therefore be accounted for when modeling such decisions.

Keywords: car-ownership, car-sharing, season ticket, mobility tool, multivariate probit, attitudes, latent variables

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1. Introduction

Arranging one’s individual transportation requires various choices at different levels, of which many are interdependent. In particular, the strategic decision to own a certain mobility tool, e.g. a car, largely determines the later tactical decisions on mode choice and therefore shapes individual travel behavior [1]. Yet, interdependencies do not only occur between the different levels of transportation choices, but also within them. For example, it has been shown that car owners are less prone to subscribe to a season ticket [2], whereas season-ticket holders in turn may be more likely to become car-sharing members [3]. In this analysis, it is assumed that the choices on mobility tools are made simultaneously. As such multiple choices may share common underlying unobserved factors and one outcome might be an endogenous factor in another outcome, jointly modeling multiple outcomes accounts for interdependencies and provides deeper insights into the decision making process [4, 5, 6, 7].

For a long time, (motor-)bikes, private vehicles and public transportation subscriptions were the only relevant mobility tools. However, in the recent years, car-sharing was established as additional option providing their members with short-term access to vehicles on an as-needed basis. The schemes attract both scientific interest and customers around the world [8].

The literature suggests that station-based car-sharing reduces private vehicle ownership as well as vehicle kilometers travelled [9, 10, 11], although there has been less agreement on the magnitude of this impact [12]. Moreover, previous research has consistently revealed that car-sharing schemes blossom best in dense urban areas with a good public transportation supply and mainly attract young, highly-educated, higher-income, urban, car-free and single-household residents [13, 14, 3].

One major limitation of previous research is that it has not sufficiently ac-

counted for the apparent causal interrelation and jointness of car-sharing membership with the ownership of other mobility tools [15]. Instead, the level of car-ownership or the availability of season tickets usually were used as possibly endogenous explanatory variables when modeling car-sharing membership.
35 This however disregards that all three are (simultaneous) outcomes of the same underlying decision process on a portfolio of mobility tools.

Another limitation is that most previous research on factors influencing car-sharing membership has mainly focused on socio-demographic factors ignoring
40 the role individual attitudes and lifestyles play in such decisions [16, 17].

This study presents an approach to model car-sharing membership as part of a portfolio of mobility tools allowing to account for both the interdependencies with other mobility tools as well as the effect of individual attitudes on car-sharing membership. In particular, the approach is supposed to shed new light
45 on travelers’ actual motivations to become car-sharing members and help to better understand the actual role, car-sharing plays in its members’ travel behavior.

The remainder of this paper is structured as follows: Section 2 provides an
50 introduction to both car-sharing and recent advances in modeling mobility tool ownership. In Section 3, the dataset used for this analysis is described. Section 4 then describes the incorporation of attitudes into the analysis, while Section 5 presents the modeling framework used for this research. In Section 6, the model results are presented. Finally, Section 7 provides a discussion of the insights
55 gained by this analysis.

2. Background

2.1. Mobility tools in Switzerland

In this research, a mobility tool is defined as an item which after a substantial down-payment provides permanent access to a certain mode of mobility
60 at low or zero marginal cost for a time-span of at least one year. Typically, Swiss residents have the choice between four such mobility tools: a car, a local season ticket, a nation-wide season ticket (GA travelcard) and a car-sharing membership. Following the definition from above, bikes and motorbikes have been omitted in this list given that they usually do not present a substantial
65 (yearly) investment and are usually not used in all of the four seasons.

In Switzerland, the most common mobility tool is the private car. It represents an average yearly investment of CHF 6 600 (average annual gross income per household: 121 000 CHF¹; 1.00 CHF = 0.70 USD²) and subsequently allows
70 inexpensive and flexible mobility at an average of CHF 0.27/km³. However, given the particularly well-developed network, public transportation in many cases is a competitive alternative to cars and in some (i.e. travel between the larger cities), it is even superior. While a GA travelcard allows for unlimited travel within the entire public transport network throughout the country, a local
75 season ticket provides access to public transportation within a defined zone or corridor. A GA travelcard has a cost similar to a car: It requires a substantial fixed investment of CHF 3 655 (2nd class) or CHF 5 970 (1st class) per year⁴ for the first family member followed by almost no marginal costs. Discounts for

¹according to household budget survey 2014: <https://www.bfs.admin.ch/bfs/en/home/statistics/economic-social-situation-population/income-consumption-wealth/household-budget.html>

²at 2015 purchasing power parity for private consumption according to OECD (2015): http://stats.oecd.org/Index.aspx?datasetcode=SNA_TABLE4

³<https://www.tcs.ch/de/auto-zweirad/auto-kaufen-verkaufen/auto-unterhaltskosten/kosten-eines-musterautos.php>

⁴prices as of 2015

additional family members apply. The least expensive option are local season
80 tickets starting at around CHF 700 per year.

The fourth option is a membership of the national car-sharing operator, which provides access to vehicles at almost 1 500 car-sharing stations throughout the country. Dating back to 1987, this station-based car-sharing scheme presents
85 an interesting case, because it is available not only in larger cities, but also in smaller towns and villages. Therefore, it is probably the only scheme worldwide offering a seamless system covering an entire country. It offers its 127 000 members access to almost 3 000 vehicles of various types at 1 500 car-sharing stations (often located at train stations or other central areas)⁵. Members can either:
90 buy a share of the cooperative (one-time investment of 1 250 CHF of which 1 000 CHF is refundable upon exit), or subscribe to the service for an annual fee of 200 to 300 CHF. The membership fee can be substantially reduced to CHF 25 for holders of a public transportation subscription, although these members pay higher rental fees. Rentals are charged both by the hour and by distance
95 travelled (currently 3 to 4 CHF/h plus 0.50 to 1.00 CHF/km, depending on the vehicle type and time of the day).

Table 1 presents the distribution of ownership of the four mobility tools. It already indicates that car-ownership and public transportation subscriptions are
100 substitutes. While car-sharing is overrepresented among holders of PT subscriptions and underrepresented among car-owners, car-sharing members are highly equipped with mobility tools, in particular GA travelcards. Also, their level of car-ownership is slightly higher than the one of holders of a PT subscription.

⁵according to the Mobility Cooperative's business report for the year 2015:
[https://www.mobility.ch/en/about-mobility/mobility-cooperative/about-us/
company-reports/](https://www.mobility.ch/en/about-mobility/mobility-cooperative/about-us/company-reports/)

Table 1: Swiss distribution of mobility tool ownership based on micro census mobility and transportation ($N = 8\,477$ - including respondents over 18 years of age and including respondents without drivers license) [18, 19].

	Car	PT subscription	GA travelcard	Car-sharing
n	5 581	1 935	736	199
Base-rate	65.8 %	22.8 %	8.7 %	2.4 %
<i>Subsets</i>				
Car-owners		13.0 %	4.6 %	1.4 %
PT subscription holders	37.5 %		38.0 %	5.0 %
GA travelcard holders	34.8 %			7.1 %
Car-sharing members	40.2 %	48.7 %	26.1 %	

2.2. Car-Sharing

105 In addition to the station-based car-sharing scheme presented above, new peer-to-peer and flexible one-way car-sharing schemes [20] have been launched in the recent years. However, earlier research shows that the actual user groups and usage patterns of such more flexible schemes are substantially different from station-based round-trip car-sharing [3]. In Switzerland, the first scheme of this
110 kind only started to operate in summer 2015. Therefore, this analysis is restricted to the traditional form, station-based round-trip car-sharing.

So far, most of the literature dealing with station-based (round-trip) car-sharing discusses the market segmentation, environmental impacts or operational issues.
115 In the stream of market segmentation, two sorts of methodological approaches have mainly been used to determine the socio-demographic characteristics of station-based car-sharing members: Most studies have used member surveys to gather socio-demographic information about car-sharing adopters and compared the results with either a control group or a population census. In addition,
120 members were usually also asked for their motivations to become car-sharing members, although those motivations were not cross-referenced to their respective socio-demographic background. Such surveys have been conducted in various (mostly industrialized) countries around the globe and consistently found

that car-sharing is particularly attractive to 25-45 year olds of higher educational levels and higher incomes living in smaller households [13, 21, 22, 3].
125 Only a small fraction of such surveys included attitudinal questions, although there is evidence that car-sharing is particularly successful in certain social milieus [23, 16, 17]. As a second approach, geographic information system (GIS)-based analyses have been used to identify neighborhood characteristics, which
130 support car-sharing membership or usage. Such studies confirmed the role of several socio-demographic characteristics and revealed the importance of public transportation access, parking pressure and population density for car-sharing adoption [24, 25].

135 Both methodological approaches have addressed the role of private vehicle ownership finding that car-sharing members are more likely to live in car-free households than their peers [14] and that car-sharing attracts households with fewer cars [11]. Moreover, earlier results indicate that car-sharing membership encourages the use of public transportation and active modes at the expense of
140 car use [11, 15, 3].

However, in none of the earlier studies, car-sharing was regarded as a mobility tool in its own right: When modeling the decision to become car-sharing member, the level of car-ownership or possession of season tickets were usually used
145 as explanatory variables although they have to be assumed endogenous to the outcome (selection-bias). Other approaches indicate that a car-sharing membership indeed triggers a general reduction in the level of car-ownership and leads to an increased use of public transportation, but the effects are usually not broken down to (potentially different) user types and again, one mobility
150 tool (this time car-sharing) is used to explain adoption of other mobility tools ignoring the underlying decision making process on a mobility portfolio.

Therefore, the actual role of car-sharing in a portfolio of mobility tools is still largely unclear. This research aims at filling this gap by studying the causal

155 background of car-sharing adoption using the Swiss micro census, the national
travel survey [18, 19]. In doing so, it also accounts for the effect of individual
attitudes on mobility tool ownership decisions.

2.3. *Modelling mobility tool ownership*

A number of static and dynamic modelling approaches exist to model own-
160 ership of mobility tools at the individual and household level. The work by
[26], [27] and [28] provides a comprehensive overview and evaluation of various
approaches. It is important to note that most of the approaches in the literature
merely address the question of car-ownership. So far, only a small number of
papers also includes other mobility tools such as motorbikes [29] or subscriptions
165 for public transportation [2, 30, 31]. Moreover, there has only been one attempt
to capture the different valuations of fixed and variable costs in car ownership
decisions [32]. In the literature, there are two ways of modelling car-ownership:
either as indicator for car availability or as number of vehicles in a household.
There is broad consensus that the second approach preserves most information
170 [28].

Although widely used in early models on car-ownership, basic multinomial or or-
dered Logit approaches [33] may yield unrealistic results when applied to model
the choice between multiple mobility tools given that the choices are not mu-
175 tually exclusive. One way to circumvent this problem is to estimate separate
binomial Logit models for each mobility tool [31] or every possible combination
of mobility tools. However, such an approach cannot capture unobserved cor-
relations between the alternatives and does not account for the fact that some
mobility tools may be used in clusters.

180

In contrast, in the multivariate Probit approach, multiple correlated binary
choice outcomes are modeled simultaneously, allowing to account for correla-
tions in the error terms between the individual choice outcomes [34] rather than
explicitly modeling each combination of choice outcomes as in the multinomial

185 case. Recent work by Bhat et al. extended the multivariate Probit to accommo-
date mixed types of outcomes, e.g. multinomial or ordered outcomes, in which
common unobserved factors and endogeneity might be present [6]. The multi-
variate Probit also allows to accommodate truncated samples [35, 36] as well as
spatial and social interaction [7].

190

Various studies have made use of the multivariate Probit approach in trans-
portation. For example, [29] applied the trivariate Probit model to describe
car, motorcycle and bicycle ownership in Osaka and Kuala Lumpur, whereas
[37] use it to study choices of shopping channels for clothing purchases. In ad-
195 dition, the bivariate ordered Probit model was used for model the number of
different mobility tools at the household level, e.g. car and motorcycle owner-
ship [38, 39] or car and season ticket ownership [30]. [40] also used a bivariate
ordered Probit model to study the frequency of use of car-sharing and ride-
sourcing services. All studies mentioned above found significant correlations
200 across choice outcomes meaning that common unobserved factors are at work.
The research presented in this paper builds upon this earlier research and uses
a multivariate Probit approach to jointly model the ownership of different kinds
of mobility tools.

3. Data

205 3.1. Swiss transportation micro census

This research is based on data from the Swiss national travel surveys (micro census) of 2005 and 2010 [18, 19]. The micro census is a quint-annual national CATI survey covering a substantial share of the Swiss population. It provides detailed information on household demographics as well as socio-economic in-
210 formation and travel patterns on the individual level for at least one household member. A share of the respondents was further asked policy questions allowing to infer individual transport policy attitudes. Table 2 presents the size of the available datasets. The micro census covers persons older than 6 years. However, for this analysis, only respondents above legal and car driving age (18
215 years) are considered.

In the micro census, the season-ticket ownership and car-sharing membership are captured on the individual level. While the car-sharing question is a simple yes/no-question, various types of public transport subscriptions are available.
220 For this analysis, a GA travelcard (1st or 2nd class), a regional season-ticket (*Verbundabo*) and a corridor-based season-ticket (*Streckenabo*) were counted as public transport subscriptions. All other options (including the half fare discount card) were neglected since they neither represent a substantial investment nor do they allow free travel in any area.

225

Car-ownership information is captured by two questions: On the household level, there is a question asking for the number of cars registered in the household (numeric), and on the individual level, there is a question asking whether the respondent had access to a car (levels: always, upon consultation, never).
230 Given its more direct effect on travel decisions, the latter variable was used in this analysis. This is in contrast to the recommendation by [28] to use the number of cars at household level, because the micro census captures disaggregate information on individual mobility tool availability for only one household mem-

ber. A car was assumed an available mobility tool if it was *always* available,
 235 the option *upon consultation* was counted as unavailable.

Table 2: Number of observations in the micro census.

Year	2005	2010
Respondents	28 785	55 060
Respondents with transport policy attitude items	3 644	5 239

3.2. Data enrichment

Although the micro census contains many variables of interest, some additional variables were constructed because they were expected to have a substantial impact on mobility tool ownership.

240

In a first step, some of those variables included in the 2010 data, but missing in the 2005 data were added to the 2005 data. This concerns mainly the level of service (micro-accessibility) of public transportation⁶ at the individual home location as well as the spatial structure at the given work place. In
 245 a second step, variables missing in both data sets were added. In particular, municipal accessibility scores (for both car and public transportation) of the individual home locations were obtained from [42]. The accessibility scores were then decomposed into three principal components describing *general accessibility*, *comparative higher accessibility of public transportation* and the *comparative*
 250 *higher accessibility to work places* [43]. In addition, the distance to the closest car-sharing station was calculated using the individual household coordinates and the station locations of the national car-sharing provider Mobility [44].

⁶The level of service was assigned based on the individual household coordinates from the micro census and a shape file with the level of service zones provided by [41]. The classification of the spatial structure was conducted based on the (available) workplace municipality code. The information was then passed through from the available information on municipality code and spatial structure from the home locations in the micro census.

Similar to other studies, also the micro census suffers from substantial item-
255 nonresponse at the household income question (2005: 20%; 2010: 17%). How-
ever, since this variable is an important predictor in most car-ownership models,
it was imputed using an ordered Logit approach.⁷

⁷Eventually, for only 36 observations, the household income remained missing. Detailed information on the imputation procedure and the OL model estimates are available from the corresponding author upon request.

4. Attitudes

4.1. Data and factor structure

260 The micro census data used for this research [18, 19] also contain self-reported attitudes towards transport policies, e.g. different forms of mobility pricing and infrastructure investments. Responses to attitudinal questions are coded in an asymmetric 3-point Likert-scale (1 = disagree; 2 = potentially agree; 3 = agree). For this research, latent constructs are calculated based on those
265 questions included in both the 2005 and the 2010 data set.

Table 3 presents the items available for the analysis. As shown in the table, there is substantial item-nonresponse leading to a final sample size of 6 952 observations (of 8 883) without imputation. However, given the strong cross-correlations
270 of certain items and the predictive power of exogenous socio-economic characteristics, an efficient imputation algorithm was implemented to maximize the available sample size (8 488 observations remain).

An exploratory factor analysis was conducted to reduce the data to the most
275 essential elements and to determine the latent constructs (number of latent variables) for the subsequent analysis. Based on the factor-Eigenvalue plot, the results of a parallel analysis and the latent-root-criterion [45], two latent variables consisting of highly related items were retained, explaining the most important dimensions of variability. The factor loadings as reported in Table 3
280 can be interpreted as correlations between the factor and corresponding items. A higher factor loading (in absolute value) means that the respective item is more representative of the factor. As shown in Table 3, the resulting factor structure is meaningful and statistically robust (acceptable goodness-of-fit measures for factor reliability and correlation structure). The two retained factors
285 may be described as follows:

- **PROFEES:** The PROFEES factor (F1) exhibits high positive loadings on items demanding the introduction or increase of road traffic fees (tunnel,

Table 3: Attitudes and factor analysis (before imputation): Pricing schemes and infrastructure improvements.

Questionnaire item	Obs.	Mean	SD	NA's	Factor F1	Factor F2
TF: Introduction of tunnel fees	7 995	1.97	0.92	928	+0.36	–
PHF: Introduction of peak hour fees	8 142	2.40	0.85	741	+0.55	–
PF: Increase in parking fees	8 198	2.55	0.78	685	+0.64	–
FP: Increase in fuel price	8 334	2.65	0.70	549	+0.63	–
PFS: Parking fees for shopping centers	8 256	2.49	0.81	627	+0.43	–
RPT: Road traffic revenues for PT infrastructure	8 302	1.48	0.77	581	–	+0.47
RR: Road traffic rev. for road infrastructure	8 303	1.37	0.69	580	–0.30	–
RSM: Road traffic rev. for slow mode infra.	8 445	1.29	0.63	438	–	+0.57
REN: Road traffic rev. for environment	8 388	1.32	0.65	495	–	+0.56

Estimation method: Maximum likelihood

Rotation method: Orthogonal varimax

Variance explained: 62.0%. Cronbach's Alpha: 0.63

Kaiser-Meyer-Olkin measure of sampling adequacy: 0.75

Likelihood-ratio test: 2 factors vs. saturated: $p < 0.000$

Number of subjects for factor analysis: 6 952

peak hour, parking and fuel) and not spending the revenues of such fees on the road infrastructure,

- **PROINFRA:** The PROINFRA factor (F2) shows positive loadings on items reflecting an inclination towards spending revenues from car fees on investments in infrastructure for public transportation and slow modes (walk and bike) or environmental protection projects.

Table 4 contains some basic summary statistics of the socio-demographic variables for $N = 8\,488$ respondents (no missing values) that are found to affect the attitudes, i.e. the factor scores of PROFEES and PROINFRA, the strongest. The socio-demographic attributes were identified using a simple correlation analysis.

4.2. MIMIC model to predict latent variables

This subsection presents the methods used to calculate the latent variables, i.e. the attitudes towards pricing schemes and infrastructure investments, which

Table 4: Socio-economic characteristics used.

Questionnaire item	Mean	SD	Min.	Max.
HHSIZE: Household size	2.36	1.31	1	10
HHINC: Household income [1000 CHF]	6.96	4.02	1.5	20
HHBIKES: Number of bikes in household	1.79	1.79	0	20
MALE: Gender [male = 1]	0.46	0.50	0	1
AGE: Age [years]	50.74	17.68	18	97
EDUC: Educ. level [above apprenticeship = 1]	0.63	0.48	0	1
LIC: Car driving license [yes = 1]	0.82	0.39	0	1
CITY: Residential location [city = 1]	0.32	0.47	0	1
TICKET: Public transport subscription [yes = 1]	0.23	0.41	0	1
FULLTIME: Working ≥ 36 h/week [yes = 1]	0.58	0.49	0	1
PARTTIME: Working < 36 h/week [yes = 1]	0.12	0.33	0	1
GER: Home in Swiss-German region [yes = 1]	0.67	0.47	0	1
FRE: Home in Swiss-Romand region [yes = 1]	0.27	0.45	0	1
ITA: Home in Swiss-Italian region [yes = 1]	0.06	0.23	0	1

are later used as explanatory variables to better describe the choice of different mobility tools. Although this sequential estimation approach is neither efficient nor consistent [46, 47], its has often shown identical qualitative implications as
305 in a simultaneous estimation approach [48].

The modeling strategy followed in this research is to first predict the two latent variables ("first-step" predictions) for the full sample, a method that relies on the rather strong assumptions of joint normality and values missing at random
310 (or the weaker assumption of covariate-dependent missingness; [49]).⁸ These "first-step" predictions are then used to impute the missing values by estimating Ordered Logit (OL) models with the attitudinal items as dependent variables.

⁸The test for joint normality of items (H_0) was rejected. However, the test for covariate-dependent missingness (H_0) of items was accepted. The modeling approach is similar to the one shown in Equations 1-4, but assumes linear instead of Ordered Logit measurement equations, which is necessary to apply the maximum likelihood with missing values approach [50]. This procedure helps to overcome the case-wise deletion of rows containing missing values.

The OL approach has the main advantage that it accounts for discrete nature of the items (3-point Likert-scales) which also are asymmetric (i.e. given the second category "potentially agree"), for which a linear measurement model would be inadequate [51]. Given that the "first-step" predictions have a high explanatory power (they are, of course, highly correlated with the corresponding items) and that only very few items of a specific respondent are missing, the imputation strategy can be assumed to be reasonably accurate.

320

Based on the factor structure and corresponding items from above, for both latent variables in Table 4, a multiple-indicator-multiple-cause (MIMIC) [52] structural equation model (SEM) [53, 54] was estimated. This was done by simultaneously modeling an OL measurement equation linking the latent variables with the items assumed to affect the latent constructs and a linear structural equation for the exogenous variables affecting the latent variables. Once the coefficients are estimated, they can be applied to predict the distribution of attitudes for a population of interest.

330 The measurement equation for latent variable $i \in \{PROFEES, PROINFRA\}$ with responses of individual n to the questionnaire items I_{att} is given by:

$$P(I_{att,n} = 1) = \frac{1}{1 + \exp(-\kappa_{att,1} + \tau_{I_{att}} LV_{i,n})} \quad (1)$$

$$P(I_{att,n} = 2) = \frac{1}{1 + \exp(-\kappa_{att,2} + \tau_{I_{att}} LV_{i,n})} - \frac{1}{1 + \exp(-\kappa_{att,1} + \tau_{I_{att}} LV_{i,n})} \quad (2)$$

$$P(I_{att,n} = 3) = 1 - \frac{1}{1 + \exp(-\kappa_{att,2} + \tau_{I_{att}} LV_{i,n})} \quad (3)$$

where $\tau_{I_{att}}$ are the latent variable coefficients for each item I_{att} (note: for identification reasons, $\tau_{I_{att}}$ for *TF* (*PROFEES*) and for *RPT* (*PROINFRA*) are fixed at 1), $LV_{i,n}$ are the latent variables and κ_{att_i} are cutoff values for each item. The structural equation for latent variable i is a function of observed socio-economic characteristics Z_n :

$$LV_{i,n} = Z_{i,n} \kappa_i + \omega_{LV_{i,n}} \quad (4)$$

where $Z_{i,n}$ is a $1 \times q$ vector of socio-economic characteristics, κ_i is a $q \times 1$ coefficient vector and $\omega_{LV_{i,n}}$ is a $n \times 1$ random disturbance vector.

Table 5 presents the results of the MIMIC model. The results of the measurement model as given in the top rows confirm the findings of the factor analysis shown in Table 3: For *PROFEES*, increasing fuel and parking prices (FP, PF) exhibit the strongest effect on the latent variable, whereas road revenues for road infrastructure improvements (RR) show the weakest (and negative) effect. For *PROINFRA*, spending road revenues on environmental protection (REN) exhibits the strongest effect. The effects of socio-economic characteristics on the latent variables are presented in the bottom rows. The model shows that increasing *PROFEES* attitudes are mainly affected by lower household size, increasing age, higher income and education, the number of bikes, season ticket ownership and living in the German-speaking part of the country. Increasing *PROINFRA* attitudes are mainly affected by being male, a lower household income, higher education, the number of bikes, season travelcard ownership and an urban home location. Finally, the correlation between *PROFEES* and *PROINFRA* of about 0.17 ($p < 0.00$) is moderate and plausible: infrastructure and environmental protection expenses have to be funded somehow and fees on car use may be regarded as a possible way to generate the necessary funds.

Table 5: MIMIC model results (N = 8 488). Variable codes as defined in Tables 3 and 4

PROFEES		PROINFRA	
Variable	Coef./(SE)	Variable	Coef./(SE)
TF	1	RPT	1
PHF	1.468***	RSM	1.339***
PF	2.207***	REM	1.793***
FP	2.255***	—	—
PFS	1.183***	—	—
RR	-0.580***	—	—
HHSIZE	-0.101***	—	—
AGE	0.007***	AGE	-0.005***
MALE	-0.117***	MALE	-0.429***
HHINC	0.018***	HHINC	-0.022***
EDUC	0.222***	EDUC	0.139**
CITY	0.254***	CITY	0.184***
HHBIKES	0.100***	HHBIKES	0.057***
PARTTIME	0.209***	FULLTIME	-0.201***
GER	0.447***	GER	-0.871***
—	—	FRE	-0.509***
σ_{L1}^2	0.906***	σ_{L2}^2	1.416***

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Note: Cutvalues κ_{att_i} not reported.

5. Model Formulation

360 For the main analysis, only holders of a drivers license are considered. The distribution of mobility tools for this subsample is presented in Table 10. Although dropping observations without drivers license may bias the general distribution of mobility tool ownership, we argue that car-sharing as a mobility tool is unavailable to non-license holders. Therefore, modeling car-sharing as mobility
365 ity tool for non-license holders would be wrong. It has to be noted that dropping responses without drivers license changes the socio-demographic composition of the sample given that the possession of a drivers license has substantial positive correlation with the household income as well as the level of education and substantial negative correlation with age. An alternative way to deal with
370 this issue would be to regard car-ownership and car-sharing membership of non-license holders as censored observations and treat them in a sample selection approach [55]. However, this approach was not pursued given that the correlation of the error terms ρ between the main regression (on car availability) and selection equation (on drivers license holding) is not significantly different from
375 zero.

Of the four mobility tools, the two season tickets are direct substitutes. Hence, modeling all four outcomes within a four-dimensional multivariate Probit approach could indicate that both mobility tools are substitutes, but would not
380 explicitly model the choice between the two of them. Therefore, the choice of season ticket is modeled in two levels: The first level determines whether an individual owns a season ticket, and the second level determines the type of the season ticket.

385 In this setup, the second-level outcome is only observed for those respondents holding a season ticket. Therefore, the model takes the form of a multivariate Probit model with sample selection, a Probit extension of the [55] model for truncated samples. Both the multivariate Probit, e.g. [6, 29, 30], and the pro-

bit with sample selection, e.g. [35, 36, 56], are well-established methodologies.

390 Also the bivariate probit with endogenous treatment is widely used in some disciplines [57, 58, 59, 60] and has recently been extended by Bhat and his colleagues to model mixed types of outcomes [61, 6].

In this research, it is assumed that Swiss residents have four choices as presented in Table 6. In the multivariate Probit formulation, each of the four choices is modeled by one equation as given in the right column in Table 6. Y_i^* is the latent propensity associated with choice i . In case $Y_i^* > 0$, the outcome is chosen, i.e. the individual owns the respective mobility tool. x_i is a vector of observed covariates and β_i a vector of coefficients to be estimated. ε_i is the error term.

Yet, the interest is not in modeling the individual choice outcomes, but

Table 6: Model equations

Number	Choice	Equation
1	Car	$Y_1^* = \beta_1 x_1 + \varepsilon_1$
2	Car sharing membership	$Y_2^* = \beta_2 x_2 + \varepsilon_2$
3	Any Season ticket	$Y_3^* = \beta_3 x_3 + \varepsilon_3$
4	GA ($Y_4 = 1$) or local season ticket ($Y_4 = 0$)	$Y_4^* = \beta_4 x_4 + \varepsilon_4$

their combination. The 12 possible outcome combinations are given in Table 7. The probability of each outcome combination is calculated by evaluating the n -dimensional multivariate cumulative density function of the normal distribution Φ_n at the point defined by the n -dimensional vector housing the latent propensities Y_i^* and the n -dimensional correlation matrix Σ_n . The correlations in Σ are informative, because a negative correlation indicates that both outcomes are substitutes, whereas a positive correlation corresponds to complements. The sample selection can be ignored if ρ_{34} is not significantly different from zero. If none of the correlations are significant, no joint modeling is required.

The vectors β_1 to β_4 and the entries of the correlation matrix Σ_4 are the

Table 7: Outcome combinations and their probabilities for car, car-sharing membership, local season ticket (LST) and GA travelcard (GA).

Number	Outcome combination	Probability	Share in obs. [%]
1	None	$P_1 = \Phi_3(-\beta_1 x_1, -\beta_2 x_2, -\beta_3 x_3; \Sigma_3)$	11.1%
2	Car	$P_2 = \Phi_3(\beta_1 x_1, -\beta_2 x_2, -\beta_3 x_3; \Sigma_3)$	69.2%
3	Car-sharing member	$P_3 = \Phi_3(-\beta_1 x_1, \beta_2 x_2, -\beta_3 x_3; \Sigma_3)$	0.7%
4	Car and car-sharing member	$P_4 = \Phi_3(\beta_1 x_1, \beta_2 x_2, -\beta_3 x_3; \Sigma_3)$	0.8%
5	LST	$P_5 = \Phi_4(-\beta_1 x_1, -\beta_2 x_2, \beta_3 x_3, -\beta_4 x_4; \Sigma_4)$	3.9%
6	LST and car	$P_6 = \Phi_4(\beta_1 x_1, -\beta_2 x_2, \beta_3 x_3, -\beta_4 x_4; \Sigma_4)$	6.6%
7	LST and car sharing member	$P_7 = \Phi_4(-\beta_1 x_1, \beta_2 x_2, \beta_3 x_3, -\beta_4 x_4; \Sigma_4)$	0.5%
8	LST, car and car sharing member	$P_8 = \Phi_4(\beta_1 x_1, \beta_2 x_2, \beta_3 x_3, -\beta_4 x_4; \Sigma_4)$	0.2%
9	GA	$P_9 = \Phi_4(-\beta_1 x_1, -\beta_2 x_2, \beta_3 x_3, \beta_4 x_4; \Sigma_4)$	2.9%
10	GA and car	$P_{10} = \Phi_4(\beta_1 x_1, -\beta_2 x_2, \beta_3 x_3, \beta_4 x_4; \Sigma_4)$	3.5%
11	GA and car-sharing member	$P_{11} = \Phi_4(-\beta_1 x_1, \beta_2 x_2, \beta_3 x_3, \beta_4 x_4; \Sigma_4)$	0.6%
12	GA, car and car-sharing member	$P_{12} = \Phi_4(\beta_1 x_1, \beta_2 x_2, \beta_3 x_3, \beta_4 x_4; \Sigma_4)$	0.2%

coefficients to be estimated. All parameters are estimated by maximum simulated likelihood [62]. The associated log-likelihood function is defined as the sum over all N individuals' chosen outcome combination probabilities P :

$$\log(\mathcal{L}(\beta, \Sigma_4)) = \sum_{i=1}^N \sum_{j=1}^{12} \delta_{ij} \log(P_{ij}) \quad (5)$$

where δ_{ij} is an indicator variable for observation i and outcome combination j . The entries of the correlation matrix Σ_4 are not estimated directly. Instead, the Cholesky factors resulting from the associated Cholesky decomposition of Σ_4 are used. The requirements for model identification follow common procedure, but the interested reader is directed to the work by [6] and [62] for a more detailed discussion. Maximum simulated likelihood estimators are consistent, asymptotically normal, and efficient if the number of draws approaches infinity faster than the square root of the number of observations [63]. For model

425 estimation in Stata⁹, the built-in option of robust standard errors was chosen.

⁹The code is available upon request.

6. Results

Following the methodology outlined above, the ownership of the four mobility tools was modeled jointly. In order to obtain the best model fit, various combinations of covariates were tested iteratively using subsamples of the data. The final model was estimated based on the complete data set (micro census 2005 and 2010, adult respondents with the attitudes-module only) using 250 random draws. Table 8 presents the results both for the multivariate Probit model and for individual univariate Probit models for comparison. However, given that Table 9 indicates significant correlations, only the results of the joint model are used for interpretation.

As shown in the table, there are significant differences between the results of the two modeling approaches, in particular in the effects of accessibility, spatial structure and the latent variables on GA travelcard holdings. Hence, using a multivariate modeling approach helps to better determine the effects of the explanatory variables. Judging from the pseudo R^2 , the univariate models achieve an explanatory power comparable to earlier studies in Switzerland [31], whereas the joint modeling approach achieves a higher explanatory power. Moreover, it is important to note that excluding respondents without a drivers license does not change the results substantially (cf. Table 11).

The model was estimated based on a pooled data set of the two micro census. This is justified by the fact that both the survey method as well as the target group (representative sample of the Swiss population) were the same. To capture general trends in mobility tool ownership, an indicator variable was included to identify observations from the later data set (2010). As shown in Table 8, the results indicate a substantial trend towards more season ticket ownership.

The results of the model draw a clear picture of how the different mobility tools

Table 8: Multivariate probit (MVP) and univariate probit (UVP) models for mobility tool ownership - drivers license holders only.

	season ticket		car		car-sharing		GA travelcard	
	MVP	UVP	MVP	UVP	MVP	UVP	MVP	UVP
Age [y]	-0.046***	-0.051***	0.014***	0.014***	-0.009***	-0.010***	-0.048***	-0.033*
Agesq [$y^2/100$]	0.041***	0.046***					0.045***	0.033*
Male			0.263***	0.274***	0.116	0.124	0.155***	0.236***
University degree (or equivalent)			0.021*	0.003	0.165*	0.177*	0.053	0.106
log household size			-0.001	0.019	-0.034	-0.062		
log household income [kCHF] per $\sqrt{householdsize}$	0.072	0.081	0.343***	0.346***	-0.044	-0.031	0.081	0.040
Main accessibility	0.107***	0.110***	-0.053**	-0.055**	0.064	0.057	0.033	-0.068*
Comp. better accessibility by transit	0.037	0.033	-0.109***	-0.110***	0.083	0.090	0.043	0.028
Comp. better accessibility to employment	1.087***	1.051***	-0.784***	-0.766***	0.200	0.229	0.372	0.420
Living and working in city center(s)	0.526***	0.531***	0.000	0.000			0.359***	-0.012
Living and working in an agglomeration			0.329***	0.307***				
Living and working in agglomeration or isolated city			0.634*	0.604*				
Living and/or working in a rural municipality			0.318***	0.300***				
PT-microaccessibility at least level B	0.135**	0.118*	-0.111*	-0.113*	0.205**	0.212*	0.029	-0.038
Distance to closest car-sharing station [km]					0.003	-0.002		
Domestic distance travelled [100km/day]			0.029	0.000			0.306***	0.366***
<i>PROINFRA</i>	0.160***	0.153***	-0.076***	-0.077***	0.068	0.079	0.130**	-0.011
<i>PROFEES</i>	0.200***	0.208***	-0.343***	-0.343***	0.382***	0.386***	0.446***	0.352***
Indicator for 2010 census	0.354***	0.358***	-0.029	-0.032	0.064	0.064	0.033	-0.115
Constant	0.170***	0.163***	-0.197	-0.209	-2.174***	-2.126***	-1.434***	-0.209
Pseudo R^2	0.37†	0.17	0.37†	0.11	0.37†	0.13	0.37†	0.10
N	6939	6939	6939	6939	6939	6939	6939	6939

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† Pseudo R^2 as calculated for the joint model

are used. For example, as shown in the four models, accessibility to both population and employment has a substantial impact on the choice of mobility tools. The better a place is accessible, the less likely households are to own a car. In turn, residents of such areas own more season tickets for public transportation.

460 The micro-accessibility of public transportation affects the choice of mobility tools in a similar way: Living in an area with a high micro-accessibility¹⁰ (i.e. levels A or B) substantially increases the propensity to hold season tickets and car-sharing memberships. With respect to car-sharing, it is interesting to note that only the effect of the micro-accessibility of public transportation is significant,

465 cant, whereas the effect of accessibility is insignificant. In addition, the results show that people who both live and work in a city are more likely to hold a local season ticket or a GA travelcard.

Furthermore, the model shows that a higher household income per capita increases the propensity to own a car or hold a GA travelcard (weakly significant).

470 In addition, people of higher education were found to be more likely to own a car or car-sharing membership. A possible interpretation of this observation is that while a higher household income allows to invest more in mobility options, professions available for highly-educated workers often require flexible commuting or travel.

475

For car ownership, not only the level of accessibility, but also the spatial structure of the municipality has a significant effect. While car-ownership is lowest for people both working and living in the centers of larger cities, living or pursuing

480 activities in the fringe of an agglomeration has a similar effect on car-ownership as rural areas. This probably reflects the usually car-centered development of

¹⁰Micro-accessibility as defined in the Swiss standard SN 640 290; level B corresponds to an equivalent of a rail station with frequent long-distance service (<10 min headway per main load direction) in <750m distance or a bus stop with frequent service (<10 min headway per main load direction) in the immediate surroundings (<300m distance).

such municipalities. Given the substantial structural differences among the five isolated cities, the corresponding effect is hard to interpret.

485 Another interesting observation is that a growing household size has a negative effect on car-ownership and car-sharing membership (although insignificant). For car-ownership, this seemingly contradicts earlier findings that household size has a positive effect on the number of vehicles per household [30, 33]. However, in this analysis, the response variable is car availability (i.e. always having
490 a car available) which likely decreases when a car is shared by more than one household member. In turn, car-sharing membership is less likely for larger households given that larger households are more likely to own a private vehicle covering also those use cases, a car-sharing vehicle would have been used for otherwise.

495 With respect to car-sharing membership, it is interesting to note that the distance to the next car-sharing station has no significant effect on the propensity of car-sharing membership (even when included as inverse, quadratic term or dummy variable). This observation may be explained by the dense network of
500 car-sharing stations covering especially those areas, which are well-connected by public transportation. Hence, the distance to a car-sharing station may be confounded with the micro-accessibility of public transportation ($\rho = 0.4$).

Of particular interest is the influence of the latent variables on the propen-
505 sities to own a given mobility tool. As the correlation between the two latent variables suggests, their effects mostly point into the same direction. Both latent variables have a positive effect on season tickets and car-sharing memberships and a negative effect on car-ownership. This is not surprising given that the variables represent attitudes either against inexpensive car use or for more in-
510 vestments into public transportation or active modes.

An important observation already at this stage is that the effect of the co-

variates discussed above on car-sharing membership is positively correlated to season ticket ownership, but negatively correlated with car-ownership.

515

The above notion is supported by an analysis of the correlations of the error terms, i.e. the unobserved effects. In particular, Table 9 shows that there is significant and substantial negative correlation between the error terms of the car-ownership equation and both the public transport subscriptions and the car-sharing membership equation. In turn, there is substantial and significant positive correlation of the error terms between the public transport subscriptions and the car-sharing membership equation. It is interesting to note that the correlations for the GA travelcard have the same sign and significance than for public transportation subscriptions. Hence, a GA travelcard appears to be an even stronger substitute for car-ownership as may even more likely be complemented by a car-sharing membership than local public transportation subscriptions.

Yet, the substantial negative correlation in both the observed and unobserved effects between car-sharing membership and car-ownership, conceal that 40.2% of the car-sharing members also own a car (c.f. Table 10). Hence, given the low share of car-sharing members among car-owners, the model results do not account for the fact that to a certain degree, car-sharing is also used as an additional household vehicle.

Table 9: Correlations in the error terms of the individual equations of the multivariate Probit model.

	Cor.	S.e.
PT subscription - car	-0.368***	(0.024)
PT subscription - car-sharing	0.208***	(0.044)
PT subscription - GA travelcard	0.923***	(0.113)
car - car-sharing	-0.357***	(0.039)
car - GA travelcard	-0.313***	(0.033)
car-sharing - GA travelcard	0.186**	(0.054)
N	8 477	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

535 7. Conclusions

The modeling approach presented above goes beyond earlier models by jointly addressing four different types of mobility tools and capturing the effect of attitudes on the individual alternatives. As presented in Table 8, the model reveals that there indeed are significant and substantial correlations in
540 the error terms of the four equations indicating that common unobserved effects are present, even after controlling for transport policy attitudes. Possible examples of such unobserved effects may be lifestyle attributes or the structure of social networks. However, independent of the actual nature of the unobserved effects, this research shows that earlier approaches without joint estimation (e.g.
545 [31]) can only provide the direction, but not the magnitude of the effects of the explanatory variables.

Another interesting observation is that there is a significant effect of the latent variables on the choice of all four mobility tools. Although the attitudes
550 to a certain degree have to be considered as endogenous [64], they do explain a substantial share of the choice behavior. Yet, the model may only be used to describe the current situation, but not to predict levels of mobility tool ownership for varying degrees of attitudes [65]. It is interesting to note that the effect of the two latent variables is similar for car-sharing membership and GA travelcard ownership in that the *PROINFRA* variable has no (highly) significant
555 effect and in that the size of the significant effect of the *PROFEES* variable is similar. This is in contrast to season ticket ownership for which the effect of *PROINFRA* is significant and positive. Hence, car-sharing members share the idea of an enhanced regulation or taxation of car use, but do not demand higher
560 investments into public transportation. Yet, it is unclear whether this is due to the fact that they already benefit from good conditions for public transportation or whether this reflects a general tendency to lower government spending. Either way, the results of this research show that the effect of individual attitudes should not be neglected when describing mobility tool ownership.

565

The results further confirm the important role of accessibilities in shaping travel behavior [66]. Although often described by spatial structure [2, 30], population density [31] or distance to the city center [29], earlier studies have consistently found lower levels of car-ownership and increased use of public transportation for people living in urban centers. However, it was also shown that accessibility (i.e. travel times to attractions) is not the only determinant, but has to be regarded in conjunction with the micro-accessibility (i.e. frequency) of public transportation as well as the spatial structure of the municipality. In particular, the results confirm earlier findings that car-sharing adoption does not depend on densities or accessibilities, but on the micro-accessibility of public transportation [24, 25]. However, the effective distance to the next available car-sharing station has no significant effect. This clearly indicates that station-based car-sharing is not used for daily travel, but to complement a public transportation lifestyle.

580

This notion is complemented by an analysis of the observed and unobserved correlations between the four equations which show a clear divide between public transportation and car-sharing on one side and car-ownership on the other side. Yet, the results may also indicate that car-sharing is not only used as supplement to public transportation, but also to a private vehicle (e.g. for occasions in which a second car is needed).

585

With respect to the general spatial and individual characteristics governing car-sharing adoption, this research allows to confirm many results of earlier research. Also here, car-sharing was found to be favored by young and highly educated customers living in small households in an area which is well-connected by public transportation [24, 25]. However, in contrast to earlier findings, a higher household income per capita does not have a significant effect on car-sharing membership.

595

Moreover, it should be noted that including land-use variables as mere exogenous variables is not accurate given that also the choice of a home location may be in itself affected by preferences for certain mobility tools [67, 68, 69].

600 This research extends earlier findings by showing that also a strong attitude against car use has a significant and substantial effect on the propensity of becoming a car-sharing member. In addition, the results clarify that car-sharing membership is independent not only from urban density, but also from accessibilities (i.e. travel times). Instead, it is the frequency of available public
605 transport connections, which has a substantial effect on car-sharing membership.

In addition, this is the first approach considering car-sharing as a mobility tool in its own right. Using this approach, it was shown that car-sharing clearly
610 works as supplement to other mobility tools, mostly public transportation. An interesting finding however is that the correlation between car-sharing membership and both public transport subscriptions is on a similar level indicating that the use cases of car-sharing vehicles rather complement than compete with public transportation.

615 A summary of the results is that both car and GA travelcard represent highly flexible mobility tools attracting affluent and frequent travelers. In turn, car-sharing appears to be a complement for holders of a season-ticket who sometimes need to travel off the public transport network and (to a lesser extent) for
620 car-owners who occasionally need a second vehicle.

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Appendix

Table 10: Distribution of mobility tool ownership ($N = 6\,939$ - drivers license holders only).

	Car	PT subscription	GA travelcard	Car-sharing
n	5 581	1 266	496	199
Base-rate	80.4 %	18.2 %	7.1 %	2.9 %
<i>Subsets</i>				
Car-owners		13.0%	4.9 %	1.4 %
PT subscription holders	57.4 %		39.2 %	7.7 %
GA travelcard holders	51.6 %			10.5 %
Car-sharing members	40.2 %	48.7 %	26.1 %	

Table 11: Multivariate probit (MVP) and univariate probit (UVP) models for mobility tool ownership - including respondents without drivers license.

	season ticket		car		car-sharing		GA travelcard	
	MVP	UVP	MVP	UVP	MVP	UVP	MVP	UVP
Age [y]	-0.044***	-0.070***	0.005***	0.006***	-0.009***	-0.010***	-0.043***	-0.031***
Agesq [$y^2/100$]	0.040***	0.064***					0.042***	0.033***
Male			0.372***	0.393***	0.140*	0.148*	0.114*	0.139*
University degree (or equivalent)			0.196***	0.198***	0.239**	0.240**	0.063	0.096
log household size			0.083**	0.111***	-0.016	-0.026		
log household income [kCHF] per $\sqrt{householdsize}$	-0.013	-0.053	0.619***	0.620***	0.036	0.056	0.052	0.080
Main accessibility	0.104***	0.107***	-0.053***	-0.055***	0.056	0.052	0.011	-0.070**
Comp. better accessibility by transit	0.034	0.026	-0.123***	-0.124***	0.079	0.082	0.128**	0.149**
Comp. better accessibility to employment	1.207***	1.157***	-0.868***	-0.849***	0.195	0.202	0.415	-0.210
Living and working in city center(s)	0.480***	0.488***	(base)	(base)			0.252**	-0.031
Living and working in agglomeration or isolated city			0.359***	0.325***				
Living and/or working in a rural municipality			0.501*	0.448*				
PT-microaccessibility at least level B			0.390***	0.363***				
Distance to closest car-sharing station [km]	0.176***	0.161***	-0.169***	-0.177***	0.183*	0.183*	0.064	-0.016
Domestic distance travelled [km/day]					0.007	0.004		
<i>PROINFRA</i>	0.155***	0.156***	0.093**	0.876**			0.004***	0.378***
<i>PROFEES</i>	0.241***	0.248***	-0.145***	-0.144***	0.060	0.062	0.111***	-0.039
Indicator for 2010 census	0.337***	0.348***	-0.304***	-0.308***	0.341***	0.347***	0.446***	0.359***
Constant	0.139***	0.131***	-0.039	-0.042	0.050	0.052	0.009	-0.089
	-0.541***	-0.021	-0.906***	-0.920***	-2.378***	-2.364***	-1.292***	-0.378
Pseudo R^2	0.23†	0.18	0.23†	0.14	0.23†	0.12	0.23†	0.10
N	8 477	8 477	8 477	8 477	8 477	8 477	8 477	8 477

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† Pseudo R^2 as calculated for the joint model