Mobility tools and use

Accessibility's role in Switzerland

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ABSTRACT

In much of Switzerland, public transport offers high levels of accessibility to workplaces and other places that make season tickets legitimate substitutes for a car. These similar patterns of accessibility provided by both modes result in high levels of correlation between the accessibility measures of both modes. This correlation almost always precludes a travel behavior analysis with several accessibility measures and cannot provide any insights into the effects of the differences in accessibility levels by both modes. We propose a principal component analysis of the accessibility measures to extract as much information as possible. We interpret the principal components obtained as: general accessibility, comparatively better accessibility by public transport and comparatively better job accessibility.

The new accessibility variables are used in a model of car and season ticket ownership and the number of car, public transport and non-motorized trips using data from the 2010 Swiss transportation microcensus. These outcomes are jointly estimated with a probit-based model for mixed types of outcomes because we anticipated simultaneous choices and that choices are dependent on each other. We find that greater levels of general accessibility, comparatively better accessibility by public transport and comparatively better job accessibility increase the probability of season ticket ownership, while the probability of car ownership decreases. We realize that ownership and use must be jointly modeled to consistently estimate the structural effects of mobility tool ownership on use.

INTRODUCTION

Mobility tools available to an individual, e.g. car or public transport season ticket, are central to his or her activity pattern and mode choice (Guo *et al.*, 2007; Eluru *et al.*, 2010; Paleti *et al.*, 2013; Le Vine *et al.*, 2013). In much of Switzerland, quality public transport makes season tickets legitimate substitutes for a car. With average annual costs of around CHF 10'000 for a car and CHF 4'000 for a nation wide season ticket, public transport offers within many cities and between the large cities similar, but more reliable travel times, e.g. the travel time from Bürkliplatz at Lake Zurich to the airport is around 22 min, while, depending on traffic, car travel times range from 16-26 min, both according to Google's journey planner. The spatial distribution of these areas can be described by concepts of the built environment (Ewing and Cervero, 2010): destination accessibility, using the private or public mode, and distance to - and quality of - public transport. The close competition of modes in Switzerland leads to similar patterns of accessibility provided by public transport and cars and results in a strong correlation of these measures. In understanding travel behavior, this correlation imposes the risk of multicollinearity. Although the choices of mobility tool ownership and use are related, the competing nature of private and public modes - measured by accessibility - in analyzing multi modal travel choices has not been prominently addressed in literature.

So far, most mobility tool ownership studies focused on car ownership (de Jong *et al.*, 2004; Anowar *et al.*, 2014), but some also included other mobility tools (e.g., Scott and Axhausen, 2006; Yamamoto, 2009); the same holds for ownership and use with a focus on cars (e.g., Bhat and Sen, 2006; Tanner and Bolduc, 2014) and less on cars and public transport (e.g., Simma and Axhausen, 2001). However, Bhat and colleagues' recently proposed methodology to jointly model mixed types of outcomes offers as a flexible framework to analyze multi modal travel choices of mobility tool ownership and use (Paleti *et al.*, 2013; Bhat *et al.*, 2014; Bhat, 2015). Regarding the competition of modes, the comparison of the accessibility by both modes has rarely attempted as most studies focused either on accessibility by car or public transport (Ewing and Cervero, 2010) and only a few combined both modes (e.g., Kuzmyak *et al.*, 2006; Shen, 2000; Scott and Axhausen, 2006; Jäggi *et al.*, 2012).

In this paper, we contribute with the proposal of a principal component analysis of correlating accessibility measures to extract as much information as possible for the analysis of mode competition in understanding travel behavior without risk of multicollinearity. We obtain a Hansen (1959)-based measure of accessibility, based on travel times from the Swiss nation-wide transport model for the private and public mode. We use the idea of Shen's 2000 general accessibility index and obtain values from a principal component analysis. From this analysis, we derive, in total, three new accessibility variables for each Swiss municipality: *general accessibility*, *comparatively better accessibility by public transport* and *comparatively better job accessibility*. These variables are used in a joint statistical model of mobility tools ownership and number of trips by car, public transport and non-motorized modes (Bhat *et al.*, 2014; Bhat, 2015). In addition to the new accessibility variables, we add two more measures of the built environment: quality of public transport at the household location and a spatial typology definition of urban center, agglomeration and countryside. In our model, we also control for socio-demographic factors such as income, age and gender to avoid the omitted variable bias.

The next section provides a literature overview in Section 3.1 on the relationship between travel and the built environment and in Section 3.2 on methodologies to analyze travel behavior. Then, we present the available data and computation of accessibility variables. In Section 5, we present the statistical model, followed by estimation results in Section 6. The paper concludes with a discussion and conclusion.

BACKGROUND

This section provides a literature overview for each of the two related fields; the volume of existing literature necessitates just a sketch. Section 3.1 addresses the relationship between the built environment and travel behavior with a focus on destination accessibility and distance to public transport, because both are relevant for this analysis. In the following, we treat destination accessibility and accessibility as synonyms. Thereafter, Section 3.2 summarizes methodologies to model travel behavior choices.

Influence of the built environment

The built environment or land-use of an area is frequently found to be a strong predictor of travel behavior. Ewing and Cervero (2001, 2010, 2017) provided extensive and comprehensive overviews on the relationship between the built environment and travel behavior. Their studies follow the *three Ds* categorization of built environment measures, as introduced by Cervero and Kockelman (1997): density, diversity and design, but also include two further *D* variables: destination accessibility and distance to - and quality of - public transport. In the following, we focus on the latter measures as they describe the interaction of the transport and land-use system relevant for this analysis.

Accessibility is a generalization of the population-over-distance relationship (Hansen, 1959) and a measure of generalized cost of travel (Weis and Axhausen, 2009). Metz (2008) argued that accessibility corresponds to the long-term benefits of transport investments. For a region with N locations, the Hansen (1959) definition of accessibility at location i links all opportunities O_j at other places j to the travel cost (time) c_{ij} of reaching these opportunities. Typically, more distant opportunities are less favored; weighting opportunities by a function of travel costs $f(c_{ij})$ considers this. A conventional formulation of accessibility is $A_i = \sum_{j=1}^{N} O_j f(c_{ij})$. Among others, the function $f(c_{ij})$ can be the inverse of travel costs or an exponential function with a negative parameter. Depending on analysis, various measures for opportunities can be used, e.g. number of employed (Hansen, 1959), population (Killer *et al.*, 2013) and housing and retail (Crozet *et al.*, 2012). Besides Hansen's definition of accessibility, other models exist, e.g. based on logit models' systematic utilities (Ben Akiva and Lerman, 1985), individuals' travel costs to their activities (Le Vine *et al.*, 2013), or the cumulative opportunities measure around a location (Handy and Niemeier, 1997). For a general discussion on accessibility perspectives, we refer the interested reader to the review by Geurs and van Wee (2004).

Ewing and Cervero (2010) reported that in general better accessibility reduces car usage, while less distance to the public transport stop favors walking and public transport use. Houston *et al.* (2014) analyzed the effect of the age of rail corridors and found less car use for older rail corridors than for newer. The effect of distance to public transport stops also is found for car ownership (e.g., Bento *et al.*, 2005; Zegras, 2010). These findings suggest the hypotheses that car ownership and use is reduced with better accessibility and better local access to public transport, while the opposite holds for public transport and walking.

Modeling travel behavior - mobility tool ownership and use

Modeling mobility tool ownership almost always means car ownership modeling (Le Vine *et al.*, 2013). Car ownership models range from aggregate level models to disaggregate household and individual level models, for which different methodologies exist to describe the decision-making process. In lieu of a comprehensive overview here, we refer to literature reviews by de Jong *et al.* (2004), de Jong and Kitamura (2009) and Anowar *et al.* (2014).

From a methodological perspective, Anowar *et al.* (2014) divided ownership models into four groups. First, exogenous static models consider ownership choices independently of other choices. These models deploy standard discrete choice models, e.g. logit, probit or the multinomial logit (MNL) (e.g., Vovsha and Petersen, 2009; Zegras, 2010; Potoglou and Kanaroglou, 2008; Karlaftis and Golias, 2002). The second group describes endogenous static models capturing other choices as well (e.g., Bhat and Guo, 2007; Cao *et al.*, 2007). The last two groups are the dynamic counterparts of the first two static model types. In particular, the third group describes exogenous dynamic models and the fourth group endogenous dynamic models, using panel data (e.g., Dargay, 2002; Nolan, 2010).

Joint modeling of multiple related outcomes, e.g. car ownership and use, is motivated by potential common, underlying, unobserved factors in the decision-making process that simultaneously affect outcomes and endogeneity. Ignoring jointness in choices can lead to inefficient estimates of effects and inconsistent estimates of structural effects (Bhat *et al.*, 2016).

Jointness can be established in several ways. First, multivariate probit-based models consider common underlying factors in multiple outcomes via error term correlation (e.g., Yamamoto, 2009; Scott and Axhausen, 2006; Andrés and Gélvez, 2014). If two outcomes exhibit a positive correlation, common underlying factors affect both outcomes in the same direction, i.e. they are complementary goods, while a negative correlation indicates substitute goods. Building on the multivariate probit, Bhat and colleagues extended the multivariate probit to model mixed types of dependent variables, e.g. nominal, ordinal, count and continuous outcomes, e.g. location, car ownership, number of trips and trip distance (Bhat *et al.*, 2014; Bhat, 2015). This modeling approach has also proved suitable for accommodating spatial or social interactions (Bhat *et al.*, 2016). Second, copula based models define linking functions between the error terms of outcomes other than the normal distribution, i.e. Gaussian copula (e.g., Spissu *et al.*, 2009). Third, in the multiple discrete-continuous extreme value (MDCEV) model (Bhat, 2005) the consumption of both, discrete goods, e.g. cars, and continuous goods, e.g. annual mileage, enters the same utility function that is maximized (e.g., Bhat and Sen, 2006; Jäggi *et al.*, 2012; Tanner and Bolduc, 2014). Last, structural equation modeling with car and season ticket ownership and their use as dependent variables offers another way to incorporate jointness (e.g., Simma and Axhausen, 2001).

DATA

Socio-economic data

Data on mobility tool ownership, number of trips and accompanying socio-demographic information is provided by the Swiss national transportation microcensus for the year 2010. The transportation microcensus is a large-scale survey carried out every five years with approximately 1 % of the Swiss population. In 2010, 59’771 households and - within these households, 62’868 individuals - were interviewed about their travel behavior (Swiss Federal Office of Statistics (BFS) and Swiss Federal Office of Spatial Development (ARE), 2012). We exclude anyone who can only move with outside support, all cases where we cannot impute the income and all cases younger than 18 from the sample. When two persons of a household reported on their travel behavior in the census, the second observation was in most cases a child. The final sample has 52’476 complete observations.

This analysis models individuals’ decision making. For each individual in the data set, we extract five dependent variables of interest, car and season ticket ownership and the number of car, public transport and non-motorized trips as follows: car ownership is defined as having a car exclusively available. All individuals without driver’s license are coded as having no car available. Season ticket ownership is defined as having any kind of season ticket subscription offering unlimited use of public transport, on either a regional or national scale. The number of trips is taken from the microcensus' travel diary, encompassing a single day. In each of the three trip variables, we pool the count outcomes of 1 and 2 trips into a single outcome and all outcomes larger than 11 to the outcome of 11. We did the first because just one trip was rarely observed and the latter because we wanted to avoid long tails in the distribution. Table 1 shows descriptive statistics of the five dependent variables in this analysis.

Table 1(a) shows that 55.96 % of all observations only have a car, 18.1 % have neither a car nor a season ticket, 15.83 % have only a season ticket and 10.11 % have both mobility tools available. For each of the three count outcomes in Table 1(b), we observe that at least 40 % of the observations reported zero trips. The total share of immobile persons in the dataset is 10.6 %. However, we cannot ignore the potential influence of soft-refusal, especially for the non-motorized trips (Madre *et al.*, 2007). The accumulation of zero trips is highest for public transport trips and lowest for car trips, which also shows the longest tail. In Table 1(c) we present the average number of trips distinguished by mobility tool ownership. Intuitively, car ownership increases the number of car trips and reduces the number of public transport and non-motorized trips, while the opposite occurs for season ticket ownership. For season ticket ownership, we observe a slight increase in the number of non-motorized trips.

TABLE 1 Statistics on the five dependent variables in the analysis of mobility tool ownership and use. Table 1(a) shows the cross tabulation of both mobility tools, Table 1(b) the frequencies of the three count outcomes and Table 1(c) the average value of the three trip variables conditional on mobility tool ownership.

(a) Jointness in mobility tool ownership, illustrated by the cross tabulation of car and season ticket ownership. Data from the Swiss transportation microcensus 2010.

Mobility tool		Season ticket No		Season ticket Yes		Total	
		N	%	N	%	N	%
Car	No	9’496	24.4	8’309	61	17’805	33.9
	Yes	29’364	75.6	5’307	39	34’671	66.1
Total		38’860	100	13’616	100	52’476	100

(b) Distribution of number of trips. Around 50 % of the population reported a car trip, while 20 % reported at least one trip by public transport. Data from the Swiss transportation microcensus 2010.

Number	Car		Public transport		Non-motorized	
	N	%	N	%	N	%
0	23’833	45.40	42’704	81.40	26’700	50.90
1 to 2	13’758	26.20	7’719	14.70	16’811	32.00
3	4’134	7.90	1’194	2.30	3’628	6.90
4	5’208	9.90	661	1.30	2’915	5.60
5	2’333	4.40	124	0.20	1’114	2.10
6	1’628	3.10	58	0.10	759	1.40
7	724	1.40	12	0.00	278	0.50
8	414	0.80	0	0.00	148	0.30
9	223	0.40	3	0.00	55	0.10
10	119	0.20	1	0.00	35	0.10
> 10	102	0.20	0	0.00	33	0.10

(c) Average number of car public transport and non-motorized trips conditional on mobility tool ownership. The ownership of a car or a season ticket corresponds to an increase in car or public transport trips, respectively. Data from the Swiss transportation microcensus 2010.

Mobility tool		Number of trips: Car	Public transport	Non-motorized modes
Car	No	0.489	0.477	1.103
	Yes	1.660	0.130	0.727
Season ticket	No	1.489	0.088	0.831
	Yes	0.616	0.701	0.922
Total		1.262	0.247	0.855

As explanatory variables, we select from the microcensus gender, age (grouped by age categories), employment status, university degree and monthly gross household income[1]. We describe the residential location of each observation by three spatial variables: first, a generalization of a Hansen (1959)-based accessibility measure that we introduce in greater detail in the next section; second, a spatial typology definition from the Swiss Federal Office of Spatial Development (ARE) *et al.* (2011) to differentiate between urban, agglomeration and non-urban environment and, third, the quality of public transport at household location. For each location, the Swiss Federal Office of Spatial Development (ARE) (2011) categorized the quality of public transport based on distance to the next station, frequency at this station and available lines on a five-level scale, ranging from from Level E (worst) to A (best). The Appendix provides a detailed description of the calculation of this scale.

We are aware of potential multicollinearity between the three variables describing residential location, but the correlations do not exceed 0.5. Table 2 shows sample summary statistics for all variables in the model. In the upper part, we list the shares of the categorical and binary variables and in the lower part, statistics of continuous predictors.

Accessibility data

The Hansen (1959)-based measure of accessibility for Switzerland is based on travel times from the 2010 national macroscopic transport models for car and public transport. In both transport models, zoning follows the municipality boundaries, except for large cities that are further subdivided. Thus, this accessibility measure is not at the household's location, but at the household's municipality level. In total, both models have 2949 zones within Switzerland. We compute for each zone / municipality i its accessibility value A_i with Equation 1.

$$A_i = log\left(\sum_{j=1}^{N} O_j \cdot exp\left(\beta c_{ij}\right)\right). \tag{1}$$

[1]We recode the stated gross monthly household income classes into a continuous scale by assigning the midpoint value of each class to the household. As 24 % of all households did not report on their income, we impute the income with an ordered logit model. For each household that did not report income, we assign the sum of the product of probability of belonging to a class with the midpoint income class value. Results available on request.

TABLE 2 Sample summary statistics

Categorical variables				
	Share			
Person is male	45.53 %			
Age categories				
> 70	16.96 %			
61-70	17.39 %			
51-60	17.59 %			
41-50	19.09 %			
31-40	15.11 %			
< 31	13.86 %			
Employed	62.26 %			
University degree	16.32 %			
Quality of public transport at household location				
Level A: very good	12.60 %			
Level B: good	16.11 %			
Level C: moderate	20.85 %			
Level D: low	26.70 %			
Level E: very low	23.76 %			
Spatial typology at household location				
City	32.50 %			
Agglomeration	48.45 %			
Countryside	19.05 %			
Continuous variables				
	Mean	SD	Min	Max
General accessibility	1.53	1.56	-10.09	5.14
Better accessibility by public transport	-0.01	0.61	-1.76	2.26
Better job accessibility	0.03	0.12	-0.40	0.42
Log of gross monthly household income in CHF	8.75	0.56	7.31	9.90

The accessibility A_i is a measure of destination accessibility to all other zones N with O_j being the number of accessible opportunities in other zones j. c_{ij} are the generalized cost of travel from i to j. The distance decay parameter β takes into account that more distant destinations are less attractive. For Switzerland, the β has been estimated for each mode by Sarlas *et al.* (2015): $\beta_{Car} = -0.261$ and $\beta_{PT} = -0.034$. The generalized cost of travel c_{ij} are equal to the in-vehicle time from i to j for each mode, but for public transport additionally contains access/ egress time, waiting time and transfers. In our analysis, we compute accessibility by both modes to the two different opportunities O_j employment and population in each municipality.

Four accessibility measures are thus available, differentiated by opportunities (population and employment) and mode to reach these opportunities (car or public transport): (1) popu-

TABLE 3 Results of the principal component analysis of the four accessibility variables

a) Summary statistics

	Component 1	Component 2	Component 3	Component 4
Eigenvalue	3.67715	.310054	.0112005	.00159724
Proportion of the Eigenvalue	0.9193	0.0775	0.0028	0.0004
Cumulative proportion	0.9193	0.9968	0.9996	1
N = 2949				

b) Loadings

	Component 1	Component 2	Component 3	Component 4
Population accessibility by car	0.5019	- 0.4697	-0.6857	-0.2394
Job accessibility by car	0.4969	- 0.5306	0.6427	0.2419
Population accessibility by public transport	0.4997	0.5099	-0.2160	0.6660
Job accessibility by public transport	0.5015	0.4877	0.2647	-0.6638

c) Correlations of factors and items

	Component 1	Component 2	Component 3	Component 4
Population accessibility by car	0.9624	-0.2615	-0.0726	-0.0096
Job accessibility by car	0.9529	-0.2955	0.0680	0.0097
Population accessibility by public transport	0.9582	0.2839	-0.0229	0.0266
Job accessibility by public transport	0.9616	0.2716	0.0280	-0.0265

lation accessibility by car, (2) job accessibility by car, (3) population accessibility by public transport, and (4) job accessibility by public transport. The four accessibility measures are a highly correlated. Arguably, both modes have a similar coverage because their infrastructures, residential areas and work places overlap. To reduce the probability of multicollinearity, we carry out a principal component analysis following the idea of Jäggi *et al.* (2012) to reduce the four variables to a meaningful scale for this analysis (Jolliffe, 2002). Results of the analysis are presented in Table 3.

A prominent criterion for the selection of the number of principal components is the Eigenvalue criterion. All components with an Eigenvalue of equal or greater than one should be selected. However, in our analysis, we find the first component exhibiting an Eigenvalue greater than one and we should selected, following this criterion, only the first component. Nevertheless, for three principal reasons we do not follow this criterion and select the first three principal components. First, we identify for the first three components an interpretation of in the context of this analysis. Second, if we would consider only the first principal component, which is highly similar to each of the four accessibility measures, the principal component analysis would be pointless because only this variable does not address the question in this analysis on how to incorporate highly correlated accessibility measures in understanding travel behavior. Third, we compared different model specifications including either only the first, the first two or the first three principal components with a likelihood ratio test and found that using all three components improves the model significantly. The first component explains more than 90 % (as measured in the proportion of the Eigenvalue) of the variation in the data and we interpret it as general accessibility. The second component explains 7.6 % of the variation and describes comparatively better accessibility by public transport and the third component explains 0.3 % of the variation in the data and describes comparatively better job accessibility. The fourth component does not have a meaningful interpretation for this analysis and is thus omitted.

After the estimation of the principal components, we predict for each traffic analysis (municipality) zone the score values for the first three components from the accessibility measures and the obtained loadings. We then merge the score values of the first three components to the observations in transportation microcensus. We use these score values as explanatory variables and to illustrate the spatial distribution of the principal components in Figure 1 and 2. Figure 1 shows that the general accessibility is highest in metropolitan regions and the densely populated Swiss plateau, but low in Alpine regions. We have added the Swiss motorway (white lines) and railway (black lines) network to the map. The zones with high levels of general accessibility overlap with motorways and dense railway networks in large parts of the country. Figure 2 shows spatial distribution of the second component, comparatively better accessibility by public transport. Again, we have added the motorway and railway network to the map. The value distribution does not follow the population distribution, as in the case of the general accessibility, but we observe that many municipalities close to the motorway network score low in this accessibility measure. The values do not score highest in centers of metropolitan regions, but in the agglomeration and countryside/ Alpine regions. We can, for example, explain high values in Alpine regions by citing existing railway and limited car networks.

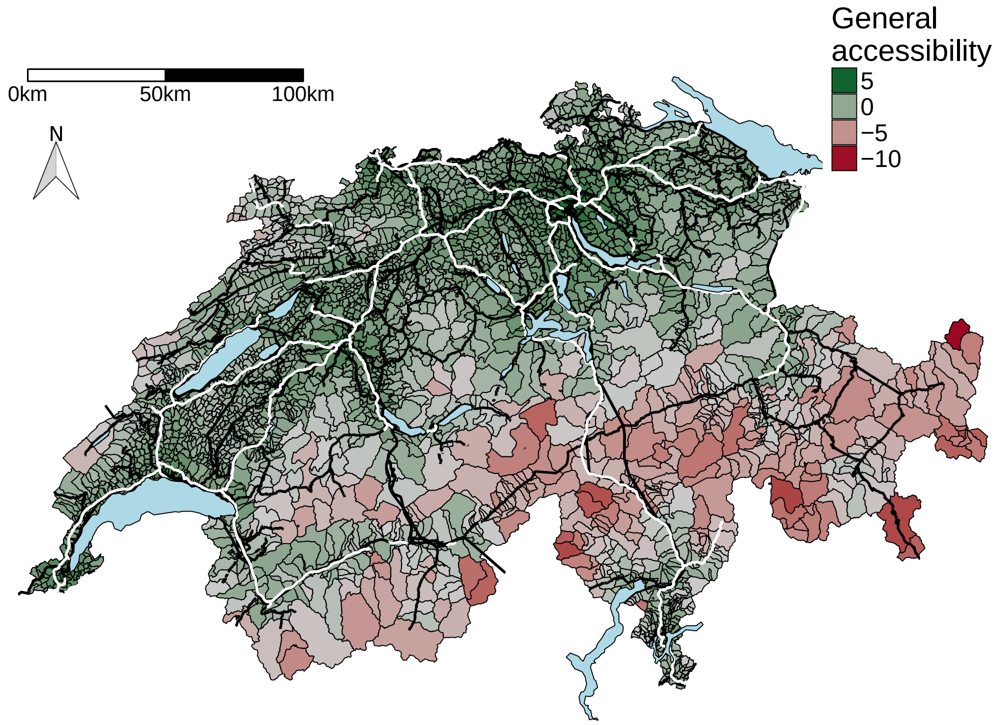

FIGURE 1 **General accessibility levels in Switzerland. The values correspond to the scores calculated from the accessibility values of each municipality and the loading from Table 3. Higher values mean greater general accessibility. The white lines show the Swiss highway network while the black lines correspond to the main railway network.**

MODEL

We model mobility tool ownership and use with a multivariate probit-based model for mixed type of outcomes, as introduced by Bhat and his colleagues (Paleti *et al.*, 2013; Bhat, 2015; Bhat *et al.*, 2016). For a detailed description, we refer the interested reader especially to Bhat *et al.* (2014). In this model, relationships between choice outcomes are established by allowing for correlations of error terms and endogenous variables' structural effects. This probit based model is an extension of the traditional multivariate probit, e.g. (Scott and Axhausen, 2006; Yamamoto, 2009; Andrés and Gélvez, 2014).

For the readers' convenience, we omit in all equations the subscript for number of the outcome equation because it appears in every outcome equation. The choice of owning a mobility tool is modeled with a binary probit. We define a latent propensity $Y^* = \beta x + \varepsilon$, with

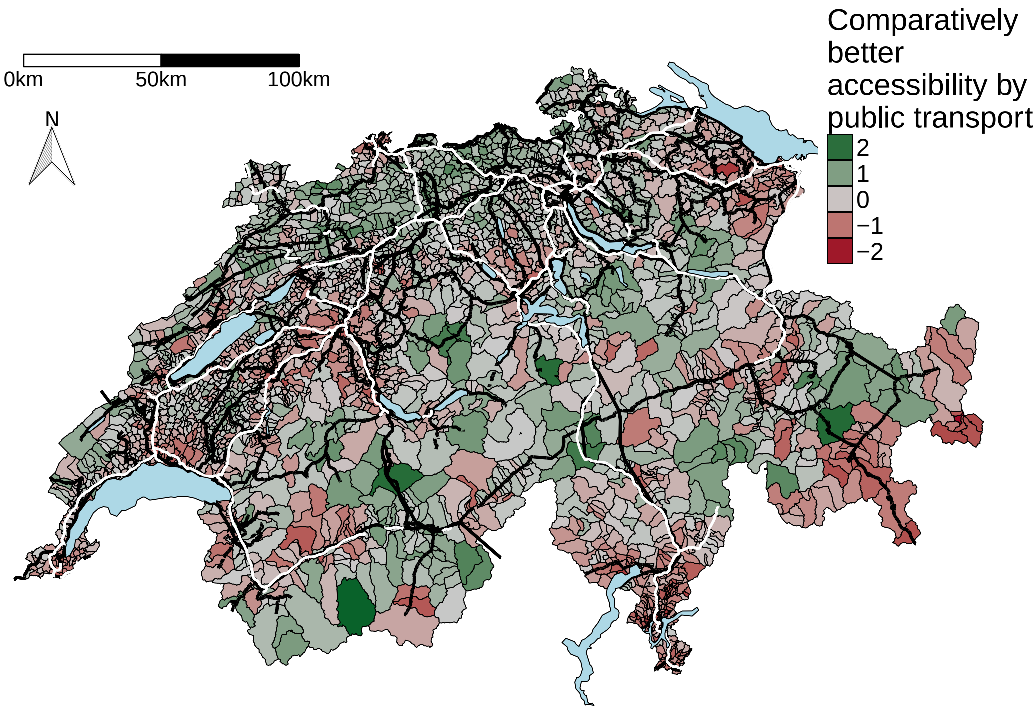

FIGURE 2 Comparatively better accessibility by public transport. The values correspond to the scores calculated from the accessibility values of each municipality and the loading from Table 3. Higher values mean comparatively better accessibility by public transport. The white lines show the Swiss highway network while the black lines correspond to the main railway network.

β a vector of coefficients to be estimated, x a vector of exogenous covariates and the normally distributed error term ε. If $Y^* > 0$, the observed outcome is chosen i.e. $Y = I(Y^* > 0)$. The outcome of number of trips is modeled as a generalized ordered probit, with more details again in Bhat *et al.* (2014) and Bhat (2015). The generalized ordered probit also has a latent propensity $Y^* = \varepsilon$, which is mapped to the observed count outcome j by threshold parameters ψ_n. For the observed count value $j = n$, the following condition holds $\psi_{n-1} < Y^* < \psi_n$. The threshold parameters ψ_n are determined by the function

$$\psi_n = \Phi^{-1}\left(\frac{(1-c)^\theta}{\Gamma(\theta)}\sum_{r=0}^{n}\left(\frac{\Gamma(\theta+r)\,c^r}{r!}\right)\right) + \varphi_n \tag{2}$$

with

$$c = \frac{exp\,(\beta x)}{exp\,(\beta x) + \theta} \tag{3}$$

Dispersion parameter θ and flexibility parameter φ in Equations 2 and 3 allow flexible count distribution modeling. Φ is the cumulative normal distribution function, Γ is the gamma function, x is a vector of exogenous and endogenous covariates and β a vector of parameters to be estimated. Error terms of each outcome equation correlate pairwise with ρ and constitute the correlation matrix P. For identification, we set $\varphi_{-1} = -\infty$, $\varphi_0 = 0$ and $\varphi_{n>0} = \varphi$ for each count outcome. The model parameters β, θ, φ and P are estimated with maximum likelihood. For each observation the likelihood is defined by

$$L\,(\beta, \theta, \phi, P) = \int_{\gamma_{low}}^{\gamma_{upp}} \phi_5\,(\tilde{u}|P)\,d\tilde{u} \tag{4}$$

The probability is obtained by integrating the five-dimensional normal density distribution ϕ_5 from γ_{low} to γ_{upp}, both five-dimensional vectors. For the binary outcome, the lower integration bound is $-\infty$ and the upper integration bound is determined by evaluating the corresponding outcome equation for Y^*. For the count outcome, the integration domain is determined by individual threshold values ψ_{n-1} and ψ_n. We use the maximum approximate composite marginal likelihood (MACML) estimator for finding the optimal parameters (Bhat and Sidharthan, 2011; Bhat *et al.*, 2014). We programmed the routine in Stata (StataCorp., 2015).

RESULTS

In Table 4, we present, for each of the five outcomes, the univariate estimates; multivariate results are shown in Table 5. Comparing univariate and multivariate estimates, it appears that the effect size differs for most covariates in the second or third significant figure, but the differences appear to be greater for mobility tool's structural effects on the number of trips. Bhat *et al.* (2014) discussed this issue. Although the univariate estimates display the same tendency as the multivariate estimates, univariate model estimates could be biased. In addition, univariate estimates cannot provide the behavioral insights generated by cross equation correlations presented in Table 6. In both the univariate and multivariate model, we find all count parameters to be significantly different from zero. Therefore, the count model is between a traditional negative binomial and a Poisson count model.

In the following, we focus on multivariate estimates and on the effects of the three spatial variables: accessibility, quality of public transport and spatial typology, as well as the structural effects. The other explanatory variables are as expected and consistent with previous research (Simma and Axhausen, 2001; Ewing and Cervero, 2010; Kowald *et al.*, 2016; Dargay *et al.*, 2007), except for two effects reported by Simma and Axhausen (2001) with data from 1994. First, the authors reported a negative effect from males on the number of public transport trips, which in our case is insignificant. Second, the authors reported an age effect on public transport trips, directly opposed to our findings.

Each of the three new derived measures of accessibility - general accessibility, comparatively better access by public transport and comparatively better job accessibility - show a negative effect on car ownership. The effects on season ticket ownership are positive for all three variables. We find, for gradually decreasing quality of public transport at household locations, likelihood of car ownership increases and likelihood of season ticket ownership decreases. In the agglomeration, car ownership is greater than in the urban center and the countryside, while car ownership is greater in rural areas than in the city center. Living in the city center shows a greater likelihood of subscribing to a season ticket than living in the agglomeration and the countryside.

For each of the three count outcomes of the number of trips we find significant structural effects of the two mobility tools. The observed differences for the number of car trips and season ticket ownership in Table 1 are replicated by the model estimates in Table 5, except for the effects of season ticket on the number of non-motorized trips. Table 1(c) show a slightly greater average of non-motorized trips for season tickets holder, but the effect in Table 5 is negative. This is anticipated because in Table 1(c) many other covariates are not considered,

TABLE 4 Univariate estimation results

	Mobility tool ownership				Number of trips					
	Car		Season ticket		Car		Public transport		Non-motorized	
Person is male	0.461***	(0.012)	−0.163***	(0.013)	0.119***	(0.012)	a		−0.083***	(0.014)
Age categories										
> 70 (base)										
61-70	0.324***	(0.021)	−0.178***	(0.022)	0.212***	(0.022)	0.222***	(0.040)	0.196***	(0.024)
51-60	0.124***	(0.024)	−0.158***	(0.025)	0.293***	(0.024)	0.331***	(0.044)	0.141***	(0.024)
41-50	0.106***	(0.024)	−0.220***	(0.026)	0.381***	(0.024)	0.294***	(0.044)	0.190***	(0.023)
31-40	0.010	(0.025)	−0.169***	(0.026)	0.366***	(0.025)	0.350***	(0.045)	0.120***	(0.025)
< 31	−0.623***	(0.024)	0.385***	(0.025)	0.506***	(0.026)	0.614***	(0.041)	−0.061*	(0.026)
Employed	0.322***	(0.017)	0.041*	(0.017)	0.310***	(0.016)	0.163***	(0.029)	a	
University degree	−0.050**	(0.018)	0.156***	(0.017)						
Quality of public transport at household location										
Level A: very good (base)										
Level B: good	0.165***	(0.022)	−0.097***	(0.022)						
Level C: moderate	0.310***	(0.024)	−0.245***	(0.024)						
Level D: low	0.415***	(0.025)	−0.348***	(0.025)						
Level E: very low	0.554***	(0.027)	−0.475***	(0.027)						
Spatial typology at household location										
City (base)										
Agglomeration	0.236***	(0.015)	−0.174***	(0.015)	0.202***	(0.014)	−0.150***	(0.023)	−0.321***	(0.016)
Countryside	0.149***	(0.022)	−0.165***	(0.023)	0.129***	(0.019)	−0.285***	(0.041)	−0.344***	(0.020)
General accessibility	−0.040***	(0.005)	0.105***	(0.006)	−0.050***	(0.004)	0.173***	(0.009)	a	
Comparatively better accessibility by public transport	−0.071***	(0.011)	0.025*	(0.011)						
Comparatively better job accessibility	−0.574***	(0.056)	0.850***	(0.059)						
Log of gross monthly household income in CHF	0.439***	(0.013)	0.038**	(0.013)						
Car always available					0.992***	(0.015)	−0.704***	(0.024)	−0.451***	(0.016)
Subscription to season ticket					−0.550***	(0.016)	1.777***	(0.025)	−0.050**	(0.017)
Constant	−4.180***	(0.106)	−0.737***	(0.107)	−0.996***	(0.024)	−2.440***	(0.041)	0.525***	(0.024)
Dispersion parameter θ					1.367***	(0.024)	1.482***	(0.103)	0.817***	(0.016)
Flexibility parameter φ					0.103***	(0.007)	0.316***	(0.019)	0.319***	(0.008)
Observations	52 476		52 476		52 476		52 476		52 476	
Log likelihood at convergence	−29 009		−27 361		−75 641		−25 986		−65 418	
Log likelihood constant only model	−33 614		−30 042		−81 353		−32 361		−66 278	
Pseudo R^2	0.137		0.089		0.070		0.190		0.013	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Estimated, but not significant different from zero.

TABLE 5 Multivariate estimation results

	Mobility tool ownership		Number of trips		
	Car	Season ticket	Car	Public transport	Non-motorized
Person is male	0.461*** (0.006)	−0.164*** (0.006)	0.118*** (0.006)	[a]	−0.087*** (0.006)
Age categories					
> 70 (base)					
61-70	0.324*** (0.009)	−0.179*** (0.011)	0.214*** (0.011)	0.217*** (0.020)	0.193*** (0.011)
51-60	0.123*** (0.011)	−0.161*** (0.012)	0.293*** (0.012)	0.325*** (0.022)	0.139*** (0.011)
41-50	0.106*** (0.011)	−0.223*** (0.013)	0.382*** (0.012)	0.286*** (0.022)	0.188*** (0.011)
31-40	0.010 (0.011)	−0.172*** (0.013)	0.367*** (0.012)	0.346*** (0.022)	0.119*** (0.011)
< 31	−0.623*** (0.011)	0.381*** (0.012)	0.503*** (0.013)	0.624*** (0.020)	−0.056*** (0.011)
Employed	0.322*** (0.007)	0.041*** (0.009)	0.307*** (0.008)	0.158*** (0.014)	[a]
University degree	−0.049*** (0.008)	0.154*** (0.009)			
Quality of public transport at household location					
Level A: very good (base)					
Level B: good	0.163*** (0.010)	−0.098*** (0.011)			
Level C: moderate	0.307*** (0.011)	−0.245*** (0.012)			
Level D: low	0.411*** (0.011)	−0.347*** (0.012)			
Level E: very low	0.548*** (0.012)	−0.473*** (0.014)			
Spatial typology at household location					
City (base)					
Agglomeration	0.237*** (0.007)	−0.174*** (0.008)	0.205*** (0.007)	−0.152*** (0.011)	−0.319*** (0.007)
Countryside	0.149*** (0.010)	−0.164*** (0.012)	0.132*** (0.009)	−0.282*** (0.021)	−0.342*** (0.009)
General accessibility	−0.040*** (0.002)	0.104*** (0.003)	−0.051*** (0.002)	0.173*** (0.004)	[a]
Comparatively better accessibility by public transport	−0.071*** (0.005)	0.025*** (0.005)			
Comparatively better job accessibility	−0.572*** (0.025)	0.848*** (0.029)			
Log of gross monthly household income in CHF	0.438*** (0.006)	0.040*** (0.006)			
Car always available			0.973*** (0.008)	−0.680*** (0.013)	−0.431*** (0.009)
Subscription to season ticket			−0.527*** (0.009)	1.749*** (0.014)	−0.053*** (0.008)
Constant	−4.166*** (0.047)	−0.747*** (0.053)	−0.984*** (0.012)	−2.438*** (0.020)	0.514*** (0.011)
Dispersion parameter θ			1.353*** (0.012)	1.447*** (0.050)	0.817*** (0.007)
Flexibility parameter φ			0.105*** (0.004)	0.319*** (0.004)	0.319*** (0.004)
Observations	52 476				
Log likelihood at convergence	−983 768				
Log likelihood constant only model	−1 051 388				
Pseudo R^2	0.064				

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Estimated, but not significant different from zero.

TABLE 6 Additional model parameter estimates

Parameter	Description		
ρ_{21}	Car and season ticket	-0.489^{***}	(0.007)
ρ_{31}	Car and car trips	-0.022^{**}	(0.008)
ρ_{41}	Car and public transport trips	0.036^{***}	(0.010)
ρ_{51}	Car and non-motorized trips	0.016^{**}	(0.006)
ρ_{32}	Season ticket and car trips	0.028^{***}	(0.008)
ρ_{42}	Season ticket and public transport trips	-0.037^{***}	(0.009)
ρ_{52}	Season ticket and non-motorized trips	-0.006	(0.008)
ρ_{43}	Car trips and public transport trips	-0.355^{***}	(0.007)
ρ_{53}	Car trips and non-motorized trips	-0.281^{***}	(0.005)
ρ_{54}	Public transport trips and non-motorized trips	-0.013	(0.008)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

e.g. spatial typology. The number of car trips increases in the countryside and even more in the agglomeration. The number of public transport trips is highest in the city center and decreases in the agglomeration and even more so in the countryside. This pattern is also observed for the number of non-motorized trips. With increasing general accessibility, the number of car trips declines and the number of public transport trips increases. The effect of general accessibility on the number of non-motorized trips is insignificant.

In Table 6, we list cross-equation parameters of all five outcomes. Except for the correlations between equations of season ticket ownership and number of non-motorized trips and between equations of the number of public transport trips and non-motorized trips, all correlations are significant. A negative correlation means that common unobserved factors affect both outcomes in opposite directions, e.g. the motivation for buying a season ticket can be contrary to having a car, while a positive correlation means that common unobserved factors affect both outcomes in the same direction. In case of an insignificant correlation, we find no common unobserved factors that affect both outcomes simultaneously. The negative correlation between car and season ticket ownership indicates that both mobility tools are substitutes. This finding is consistent with previous findings (Scott and Axhausen, 2006). Correlation between number of car and public transport trips and between car and non-motorized trips is negative, indicating that these types of travel are substitutes.

The values of all significant correlations that represent the structural effects between mobility tools and number trips are less than 0.1 in magnitude. We find that the correlation between car ownership and car trips as well as season ticket ownership and public transport trips is negative.

We expect that, in both cases, the negative correlations might capture unobserved factors such as the impetus to use the mobility tool due to a large financial commitment. For positive correlations of structural effects, we assume they might describe a general factor of demanding mobility. To validate the negative correlations for the two structural effects, we estimate Poisson and linear regression models with endogenous mobility tool ownership and also find negative correlations. We conclude that joint modeling of outcomes is necessary, because most cross-equation correlations are significant. Thus, univariate estimates are biased.

DISCUSSION

We find that our results are consistent with previous findings, e.g. for the effects of the built environment (Ewing and Cervero, 2010) and for Switzerland (Simma and Axhausen, 2001; Kowald *et al.*, 2016). However, we have to address certain methodological and data issues.

We decided to jointly model car and season ticket ownership, as well as the number of car trips, public transport and non-motorized modes for two main reasons. First, public transport is, in most regions of Switzerland, an attractive alternative to a car. Thus, we expect that the choice between both mobility tools is therefore made simultaneously. Second, owning a mobility tool is a large financial commitment to a mode and therefore a powerful predictor of using that mode. Therefore, the ownership of a mobility tool is endogenous. Based on these reasons, we decided to use Bhat's probit-based model for mixed types of outcomes; see Bhat *et al.* (2014) and Bhat (2015). However, we could also have applied other methodologies to compare our estimates. With interest only in mobility tool ownership, we could have modeled the decision making process with a multivariate probit (e.g., Yamamoto, 2009), or a multinomial logit (e.g., Vovsha and Petersen, 2009; Kowald *et al.*, 2016). For the combination of jointly modeling ownership and travel activity, we could also have used copula based models (Spissu *et al.*, 2009) or allowed for complementary and substitution patterns in multiple discrete continuous models (Bhat *et al.*, 2015).

With the joint modeling approach, we also tried to capture not only the structural effects of ownership on use, but also the commitment or lock-in in the correlation matrix of the unobserved factors. However, in future research we have to consider these effects with special focus on the influence of residential location choice (self-selection), attitudes and spatial interactions (Mokhtarian and Cao, 2008; Cao *et al.*, 2009; Ewing and Cervero, 2010; Bhat *et al.*, 2016). In addition, we can extend this analysis to the influence of the workplace location for the employed. Last, we could consider instead of the number of trips the distance or time traveled by mode using Copula or multiple discrete-continuous extreme value models

Finally, we estimated model parameters using the maximum approximate composite marginal likelihood (MACML)(Bhat *et al.*, 2010; Bhat and Sidharthan, 2011), for which Bhat *et al.* (2010) reported that the MACML approach recovers estimates just as well as the simulation approach and that reduction in efficiency by the marginal compared to the simulation approach is “in the range of nonexistent to small”. However, we could also use the simulation approach (Train, 2003) to compare the estimates and to obtain more insights into the question of whether the univariate estimates are biased.

In this analysis, we used data from the Swiss transportation microcensus offering a one-day travel diary. We could estimate this model using a multiple day travel diary (e.g., Zimmermann *et al.*, 2001), to recover more effects from the data: for example, linking activities to trips and adding the activity-based accessibility measure introduced by Le Vine *et al.* (2013). The model could also be expanded by using spatial information on each trip’s start and end points, to estimate the effect of start and end locations on mode choice. In Switzerland, there are different options for buying a season ticket, i.e. local or nation-wide. In future research, we could distinguish between ticket types (see Loder and Axhausen, 2016; Becker *et al.*, 2017), but also validate the negative error correlation for the structural effects of car ownership and car trips, as well as season ticket and public transport trips using other data sets. Last, the introduced accessibility measure makes it difficult to predict how changes in accessibility by one mode affect all choices. When making predictions under these circumstances, researchers must change the input accessibility variable and transform it with component loadings before forecasting.

CONCLUSIONS

In this paper, we present an approach to accommodate highly-correlated destination accessibility measures in travel behavior models, carrying out a principal component analysis on the accessibility measures and using the principal components in the modeling instead. We use the new accessibility variables as explanatory variables in modeling mobility tool ownership and number of car, public transport and non-motorized trips in Switzerland, employing a multivariate probit-based model for mixed types of outcomes (Bhat *et al.*, 2014). We found with a likelihood ratio test that the joint modeling approach improves the model significantly when compared to a model with the correlation matrix constraint to the identity matrix. Furthermore, we scrutinized the fit of the model by investigating the log likelihood for outliers (Ben Akiva and Lerman, 1985). In the distribution we observe that 10 % of the sample have a likelihood value several magnitudes away from the mean and median. We checked the extreme cases for consistency but did not experience conflicting outcomes. Further, we checked the sensitivity of the estimates when removing the most extreme outliers (less than 1 %) but did not find noticeable changes.

The model results show the expected signs that increasing general accessibility, comparatively better accessibility by public transport and comparatively better job accessibility reduces the probability of car ownership and increases the probability of season ticket ownership. Structural effects of mobility tool ownership on number of trips show the expected signs, e.g. car ownership increases the number of car trips. We observe that car and season ticket ownership are substitutes, as well as car and public transport trips. The effects of our other control variables in the model are consistent with previous research (Simma and Axhausen, 2001; Scott and Axhausen, 2006; Kowald *et al.*, 2016). We conclude that jointly estimating mobility tool ownership and number of trips is necessary to avoid a bias in the estimated effects and to recover common unobserved factors affecting multiple outcomes.

The proposed approach for deriving accessibility measures through principal component analysis is of interest for all researchers in the field of built environment and modeling travel behavior. The model estimates are important for Swiss transport planners, because we present the first joint mobility tool ownership and travel activity model covering the private, public and non-motorized mode.

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TABLE 7 Public transport stop classification

	Means of transportation			
Headway	Rail junction	Rail	Tram, bus, ship	Cablecar
<5min	I	I	II	V
5-10min	I	II	III	V
10-20min	II	III	IV	V
20-40min	III	IV	V	V
40-60min	IV	V	V	V

APPENDIX

Calculation of the local access to public transport measure

The five level scale of the local access to public transport is obtained as follows. First, each public transport stop is characterized by means of transportation and headway on a five level scale from I to V according to Table 7. For multiple means of transportation at a stop, the lowest value is chosen. For the estimation of the local access, the above classification is paired with each household's distance to this stop according to Table 8. For each household, the best stop determines the level. All households located farther away than 1000m from the next stop are classified in Level E.

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TABLE 8 Classification of the level of access to public transport

	Distance to the transport stop from the household location			
Stop classification	< 300m	300-500m	501-750m	751-1000m
I	Level A	Level A	Level B	Level C
II	Level A	Level B	Level C	Level D
III	Level B	Level C	Level D	Level E
IV	Level C	Level D	Level E	Level E
V	Level D	Level E	Level E	Level E

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