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Modelling free-floating car-sharing use in Switzerland: A spatial regression and conditional logit approach

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Abstract

Free-floating car-sharing has been one of the latest innovations in the car-sharing market. It allows its customers to locate available vehicles via a smartphone app and reserve them for a short time prior to their rental. Because it is available for point-to-point trips, free-floating car-sharing is not only an alternative to private cars, but also to public transportation. Using spatial regression and conditional logit analysis of original transaction data of a free-floating car-sharing scheme in Switzerland, this research shows that free-floating car-sharing is mainly used for discretionary trips, for which only substantially inferior public transportation alternatives are available. In contrast to station-based car-sharing, it does not rely on high-quality local public transportation access, but bridges gaps in the existing public transportation network.

Keywords: free-floating car-sharing, one-way car-sharing, GPS tracking, booking data, mode choice, spatial regression, usage patterns

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1. Introduction

Free-floating car-sharing has been one of the latest innovations in the car-sharing market. It allows customers to locate available vehicles via a smartphone app and reserve them for a short time prior to their rental (typically 15 min). At the end, customers may leave the vehicle at an eligible on-street parking space within a pre-defined (typically city-wide) service area. It therefore offers flexible one-way trips and has been able to attract new customer groups for car-sharing [1]. Moreover, because it is available for point-to-point trips, free-floating car-sharing is attractive not only as an alternative to private cars, but also to active modes and public transportation. However, little is known about the actual use cases of free-floating car-sharing so far.

Although there is substantial growth of free-floating car-sharing around the globe, a number of cities have already seen a cessation of operations of such schemes allegedly due to a lack of profitability [2, 3]. It appears that even after several years on the market, it is largely unclear, which factors govern free-floating car-sharing demand.

This research uses transaction data of a free-floating car-sharing operator to better understand the market niche of free-floating car-sharing. It does so by studying the effect of neighborhood characteristics on free-floating car-sharing demand in a spatial regression approach and by studying the effect of trip attributes in a mode choice model. The analysis is conducted for the city of Basel, where at the time of this research, a car-sharing operator provides 120 free-floating vehicles. Although the city's agglomeration extends into Germany and France, the main service area only spans the city of Basel as well as a number of adjacent municipalities in Switzerland. In addition, there is an outpost of the service area at the tri-national airport, which is located in France. Within the service area, car-sharing customers may use any free or residential on-street parking as well as dedicated parking spaces at the main train station and the airport. In total, the on-street parking spaces avaialble for the car-sharing scheme correspond to about 82% of the total number of on-street parking spaces in the city.

2. Background

Apart from a few experimental set-ups, car-sharing has for a long time been offered as station-based service only. In this setting, customers can reserve a vehicle, take it from a fixed parking space and use it for the reserved period of time. Most of such schemes are operated as return-trip schemes meaning that at the end of the rental, the vehicle needs to be brought back to the point of departure.

Station-based round-trip car-sharing schemes are already quite well understood. For example, it has consistently been found that round-trip car-sharing is most likely to be adopted in dense urban areas, which are well connected by public transportation [4]. It was also found, that younger, highly educated and car-free households are most likely to become car-sharing members [5]. Moreover, there is agreement that car-sharing facilitates a car-free lifestyle by providing a vehicle in situations, in which it is actually needed [6]. This way, it helps to reduce car-ownership and vehicle miles travelled [7, 8].

Whilst most of the empirical research on round-trip car-sharing was based on member surveys, a few studies used geo-information to complement insights from those surveys. For example, Celsor and Millard-Ball [9] studied the socio-demographic composition of census blocks adjacent to car-sharing stations. Their results suggest that neighborhood characteristics are even more important to car-sharing success than individual members' demographics. In particular, they suggest that part of the local car-sharing demand can be predicted by the average household vehicle ownership as well as the mode share of walk among commuters in a given area. The findings were extended by Stillwater et al. [10] showing that also characteristics of the built environment, particularly street width and public transportation service levels significantly affect local demand for station-based car-sharing. Including land-use variables in their model, Kang et al. [11] point out that car-sharing is used more intensively in business districts and areas with a high density of car-sharing stations.

However, they also find that in Seoul, station-based round-trip car-sharing is most successful in areas featuring higher vehicle ownership rates and less rail accessibility indicating substantial differences in car-sharing adoption and use between Asia and the North America.

Using transaction data and the monthly usage and availability as dependent variables, de Lorimier and El-Geneidy [12] confirm, that the number of vehicles parked at a given car-sharing station and the number of car-sharing members living in the vicinity have a strong positive effect on use. However, they also find large seasonal variation in car-sharing use.

In a different approach, Leclerc et al. [13] also used vehicle tracking to better understand usage of station-based round-trip car-sharing schemes. In particular, they have found that car-sharing tours contain more trips than tours made with private cars. Moreover, the stops are shorter indicating a more efficient use of the vehicle.

To better understand use cases of round-trip car-sharing, Ciari and Axhausen [14] analyzed stated preference data from a national survey in Switzerland. Using a multinomial logit approach, they showed that while in general, round-trip car-sharing is more attractive than public transportation, access to car-sharing stations is perceived particularly burdensome.

Free-floating car-sharing operates without fixed car-sharing stations and return trip requirements. Due to such structural differences, it was found to attract different customer groups and to also have a different impact on travel behavior [15, 16]. Therefore, knowledge about the drivers of station-based car-sharing demand as outlined above may not be applicable to free-floating car-sharing.

In a first approach to better understand free-floating car-sharing adoption, Kortum and Machemehl [17] analyzed transaction data of a free-floating car-sharing scheme in Austin, TX. By combining the transaction data with spatial information on the rental start points, they found that free-floating car-sharing is particularly often used in neighborhoods with a high population density, a high share of younger (aged between 20 and 40 years) and male inhabitants as well as smaller household sizes. Using a similar approach for Berlin and Munich, Schmöller et al. [18] were able to confirm that free-floating car-sharing is most heavily used in areas with young residents living in smaller households. In addition, higher residential rents and a high density of businesses (including offices, shops, restaurants and bars) were found to have a positive effect on car-sharing utilization. They also found high short-term variations in demand, which may partly be explained by weather effects. However, by using simple linear regression models to study the effect of neighborhood characteristics, both approaches neglect spatial autocorrelation, which may lead to bias in the respective results.

Moreover, given that Swiss cities are substantially smaller than most other European and North American cities featuring free-floating car-sharing schemes, it is unclear, whether there are different drivers of car-sharing demand. To this end, an extended version of the approach by Kortum [17] and Schmöller [18] is used to study, which spatial attributes have an effect on long-term demand for free-floating car-sharing. The insights are then complemented by a mode choice model to better understand short-term variations in this demand.

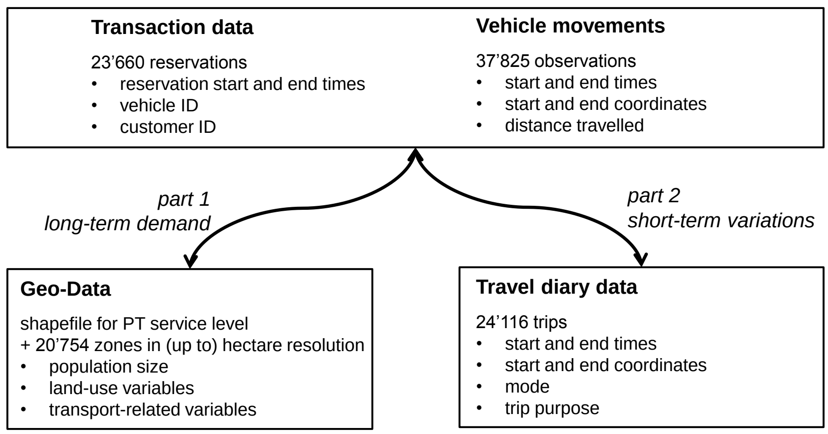

Figure 1: Data sets used in this research

3. Data

This research builds on data sets from different sources as shown in Figure 1. In the following, the origin and scope of the individual data sets are described in more detail.

3.1. Free-floating transaction and vehicle data

The backbone of this research is transaction and vehicle data provided by the free-floating car-sharing operator in Basel. In total, information on 23 660 transactions and 37 825 vehicle movements undertaken by the scheme's customers were available.[1] The transaction data contained information about the start and end times of the reservation as well as a vehicle identifier and an anonymized customer ID. The vehicle data in turn provided information on the start and end addresses of each movement (the criterion was engine turn-off) as well as the respective departure and arrival times for each vehicle. Moreover, it contained information on the driven distance, although no intermediate waypoints were available.

[1]Service trips undertaken by the operator's staff were also available, but were excluded from the analysis.

Since no common identifier was available to link the two datasets, they were matched by time and vehicle ID: every vehicle movement that occurred between five minutes prior and five minuted after a given rental were assigned to this rental. For 1 510 vehicle movements, no corresponding reservation was found. However, given that these vehicle movements were not significantly different (at the 10% significance level) with respect to distance traveled, travel time and time of day from the ones with a reservation record, the missingness was assumed to be random and the vehicle movements without reservation record were omitted. Another 216 vehicle movements were excluded, because they were shorter than 50 meters. Eventually, 36 099 vehicle movements in 23 660 reservations remain available for the analysis.

Finally, for each of the vehicle trips, the corresponding start and end addresses were geo-coded using the GoogleMaps GeoCoding API [19]. Due to technical reasons, however, geo-coding was not possible for 1 029 reservations due to ambivalent address identifiers in the data set. This is also why the airport was not reliably identified in the vehicle data. Given that the service area was extended to cover the airport at a relatively late point in time, which was also after the start of the records of the vehicle data, the airport was not considered as part of the free-floating car-sharing service area in this analysis. Hence, this research focuses on the analysis of the role of free-floating car-sharing in day-to-day intra-city travel behavior.

3.2. Geo-Data

To allow an identification of external drivers of car-sharing demand, geo-spatial data from the Cantonal transport model was provided by the Canton of Basel-Stadt. The data includes a number of socio-demographic, land-use as well as transport-related variables for the whole region of Basel in (up to) hectare resolution [20]. 13 320 of the 20 754 zones of the transport model lie within the service area of the car-sharing scheme.

Moreover, a shapefile of the service levels of public transport was obtained from both the Canton of Basel-Stadt and the Canton of Basel-Land.

3.3. Travel diary data

Electronic travel diary data of free-floating car-sharing members were available from a related study in the area [21]. In total, 24 116 trips of 678 respondents were available for this analysis. The trips were recorded in the months October to December and April/May (hence, during fall and spring), so that the seasons generally match the origin of the transaction and vehicle data. The observations are almost uniformly distributed over the week (around 15% per day except for Sundays (10%)). Trip information includes GPS positions of start and end points of the trip, the exact start date and time, the distance travelled as well as the transport mode.[2] In addition, socio-demographic information as well as information on mobility tool ownership is available for each respondent. However, the data set includes an only insignificant number of trips conducted by free-floating car-sharing.

[2] A trip is defined as travel between two activities. In case multiple modes are involved, the main mode is reported; if more than one main mode is involved (such as car-sharing and train), the corresponding stages are reported separately.

4. External drivers of intensity of use

In a first step, the transaction data of the free-floating car-sharing scheme was combined with the geo-data from the two Cantons of Basel to study the effect of spatial characteristics on free-floating car-sharing demand.

4.1. Methodology

For the following analysis, 4 599 observations were dropped from the vehicle data, because they were recorded almost one year before the bulk of the observations and the service area was expanded substantially within that year. The remaining observations are from a continuous time stretch during which the service area and price levels of the free-floating car-sharing scheme remained unchanged. The start points of the remaining rentals from the vehicle data were then matched to the hectare-resolution geo-data from the Cantonal transport model. The matched data was subsequently enriched with additional information as described in the following.

For each centroid of the hectare raster, the local service level of public transportation as defined in the Swiss standard SN 640 290 was determined using data provided by the Cantons of Basel-Stadt and Basel-Land. Thereafter, the number of free-floating car-sharing members residing in each hectare-zone was determined using data from an earlier study in the same area [16]. The addresses reflect the status just before the first observation of the reduced set of vehicle data.

None of the available data sets contains accessibility information. However, accessibility is known to trigger economic activity and therefore travel demand [22]. Thus a rough estimate of accessibility was calculated and added to the data set. The calculation followed the original formulation suggested by [22]:

$$A_i = \sum_{j \neq i} \frac{w_j}{d_{i,j}}$$

where $d_{i,j}$ denotes the Haversine distance between the centroids of the two zones and w_i in one case represents the number of inhabitants and in a second case represents the number of workplaces in the given zone. Although more advanced formulations of accessibility are available [23], they were not used in this research as they would require routed travel times or other detailed attributes, which were not available from the given data sets. Still, the accessibility scores calculated in this simplified way provide a valid representation of the relative location of the zone in the city.

Eventually, all 1 567 observations starting outside of the main free-floating car-sharing service area were omitted. The data set was then analyzed using various regression techniques based on the `R` functions `lm` [24] and `spreg` [25].

Table 1: List of Attributes for spatial model. Levels of correlation are presented in Figure 3

Variable	Type	Description
highPT	factor	zone features high level of transit service (level A or B)
ln(PopAcc)	numeric	population-weighted accessibility as described in the text (logarithmic)
PopSize	numeric	number of inhabitants aged between 25 and 64 years divided by 1 000
WP	numeric	work places divided by 1 000
PTticket	numeric	share of season-ticket holders
Cars	numeric	number of registered cars per inhabitant
FFCS	numeric	share of free-floating car-sharing members per 1 000 inhabitants
modeSharePT	numeric	transit mode share among trips originating in the area according to the cantonal transport model
modeShareCar	numeric	car mode share among trips originating in the area according to the cantonal transport model

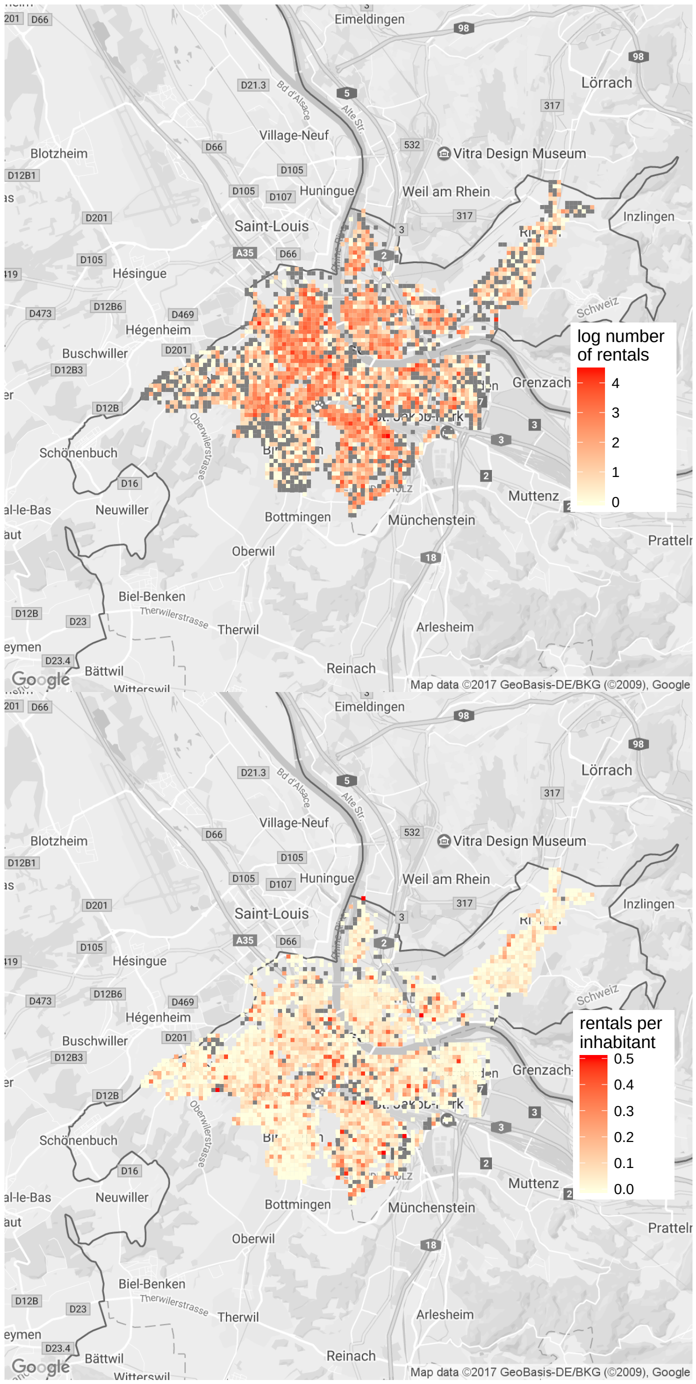

Figure 2: Free-floating car-sharing rentals per hectare

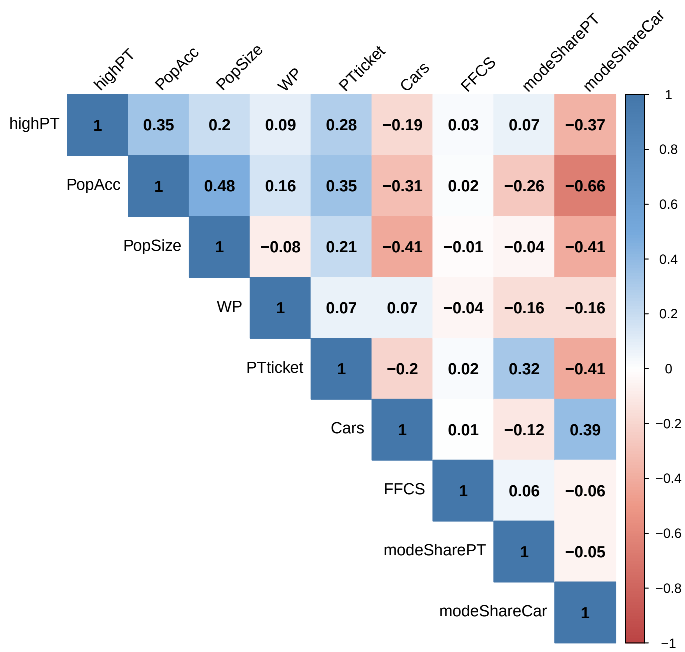

Figure 3: Correlation matrix of spatial attributes

4.2. Results

Figure 2 shows the distribution of rental start points over the city of Basel. From the upper part of the figure, it becomes clear that the rental start points are not uniformly distributed within the service area, but are mostly concentrated along an axis from the north-west to the south-east, i.e. between the Kannenfeld and the Bruderholz quarter. In the lower part, the number of rentals per hectare was divided by the number of inhabitants to reveal areas with a particularly high intensity of use. The plot indicates a particularly high usage around the main train station as well as in the southern and western suburbs. Yet, other spatial attributes may also play a role.

As a first step to understand the actual drivers of free-floating car-sharing demand, a linear regression model has been estimated using maximum likelihood. However, the model is not valid given a significant level of spatial autocorrelation of the residuals (Moran I standard deviate = 10.07, $p < 2.2 \cdot 10^{-16}$).

Given that a Lagrange-Multiplier test [26] indicates significant spatial dependence for both the dependent variable and the disturbances ($\text{LM}_{err} = 163.42$, df= 1, $p < 2.2 \cdot 10^{-16}$; $\text{LM}_{lag} = 194.91$, df= 1, $p < 2.2 \cdot 10^{-16}$), a linear Cliff-and-Ord-type [27] SARAR model of the form

$$y = \lambda W y + X\beta + u$$

$$u = \rho W u + e$$

with $e \sim N(0, \sigma_i^2)$ has been estimated, where W denotes the row-standardized spatial weights matrix for 24 nearest neighbors. The 24 nearest neighboring zones represent all neighboring zones closer than 300 meters, which is assumed an acceptable walking distance to a free-floating car-sharing vehicle. The model formulation assumes that the number of departures in a given zone not only depends on the spatial characteristics of this zone, but also on the number of departures in adjacent zones (local spillovers). Moreover, the model captures spatial autocorrelation in the error terms, i.e. assuming spatial clustering of the unobserved effects. From a behavioral standpoint it is intuitive that there is spatial clustering in the unobserved effects given that the model includes only a limited number of explanatory variables leaving space for unobserved effects (e.g. cinemas, concert halls, shopping centers), which affect the level of demand in their surroundings. In contrast, an interpretation of the spatial lag of the dependent variable is less immediate. However, one may argue that a high number of departures in a given hectare zone may eventually drain supply of vehicles in that zone, so that the demand spills over to adjacent zones.

Given the large number of observations, a maximum likelihood estimation of the model is not feasible in this case [28]. Therefore, the model was estimated using a general method of moments approach. Table 1 summarizes the attributes used in the final model, Figure 3 presents the respective correlation matrix. As can be seen from the plot, there is substantial correlation between accessibility and car mode share. Yet, the plot does not hint at multicollinearity issues. The results are presented in Table 2. The model offers a better fit than the simple model described above ($AIC_{\text{spatial model}} = 5\,163$ compared to $AIC_{\text{linear model}} = 5\,259$).

The model reveals that - as suggested by Figure 2 - a substantial share of the variance can be explained by the population size of an area. Also the share of free-floating car-sharing members residing in an area has a highly significant positive impact on the number of departures in that area. In contrast, the intensity of free-floating car-sharing use is inverse to an area's number of work places and accessibility score.

In addition, the model indicates that areas experiencing a high share of departures with motorized modes (car and public transportation) see less free-floating car-sharing activity.

It is also important to note that a number of spatial variables were not found to have a significant effect on the number of free-floating car-sharing departures. Among those are the work place-weighted accessibility, the distribution of mobility tools (cars, season tickets), retail space, parking costs or proximity to the main train station as well as to the university campus. Moreover, some variables, in particular gender distribution and household sizes, were not available.

Table 2: Spatial regression model for free-floating car-sharing demand. Please refer to Table 1 for a description of the variables.

	Coef.		t
number of departures			
highPT	0.26		0.53
PopAcc	-3.78	**	-2.25
PopSize	27.60	***	6.93
WP	-2.89	***	-2.74
PTticket	0.58		0.64
Cars	0.23		0.25
FFCS	0.05	***	8.49
modeSharePT	-3.90	**	-2.24
modeShareCar	-3.45	**	-2.35
(Intercept)	47.30	**	2.28
λ	0.76	***	11.70
ρ	-0.50	***	-3.39
N	2 664		
AIC	5 163		

Significance codes: 0.10 * 0.05 ** 0.01 ***

5. Free-floating car-sharing mode choice

To better understand the short-term variations in free-floating car-sharing demand, a mode choice model for free-floating car-sharing was developed. Given the flexible nature of free-floating car-sharing, it is assumed that the decision to use it needs to be modeled on the trip level.

5.1. Methodology

The following analysis is based on the vehicle data. However, it is impossible to estimate any choice model based on a data set in which only one alternative (car-sharing) is chosen and observed. To overcome the constraint of missing variation in choice, the vehicle data was pooled with the travel diary data of free-floating car-sharing members. The pooled dataset then contains of 35 070 vehicle trips and 24 116 trips from the diary. It includes technical information on the respective trip (such as start and end points and times, distance travelled) and an anonymized customer ID, but no further details (such as any socio-demographic attributes).

In a next step, the choice set was defined. In principle, free-floating customers can choose mainly between free-floating car-sharing, walk, bike, public transportation, taxi and their private car. However, given that not all of the alternatives were necessarily available or considered in the given choice situation, the choice set had to be reduced to a more realistic representation. A preferable way to do so would be to apply a two-stage approach, i.e. to first estimate individual consideration sets based on which then the actual choice model is estimated [29]. However, given the lack of any further information on the decision makers' socio-demographic characteristics or more detailed trip information such as purpose or group size, the actual choice set had to be defined in a deterministic way. The reasoning is as follows: On the trip level, a private car can be seen as a dominant alternative to free-floating car-sharing, because it has a lower marginal cost per minute/kilometer and parking prices are either relatively low or inexistent in the Basel area. Therefore, it is assumed that free-floating car-sharing is used only if a private car is unavailable for the given trip or if the tour contains an earlier or later trip, which cannot be performed by car.[3] Therefore, car is excluded from the choice set. In addition, taxi had to be excluded because of the low number of corresponding observations (56 out of 24 116).

In contrast to car and taxi, it was less clear how to properly deal with the bike alternative. It has to be noted that excluding bike from the choice set is a substantially stronger assumption than excluding car, because bike is not a dominant alternative and only 7.3% of the members of the free-floating car-sharing scheme do not own a bike [16]. However, only a minority of free-floating car-sharing members was found to use a bike on a daily basis. Moreover, like a car, a bike has to be carried through all trips of a (sub-)tour if chosen for the first trip. Hence, not only do the attributes of the specific trip play a role, but also the attributes of the preceding and/or successive trips, which are not available in this data set. Also, this is unlike free-floating car-sharing, public transportation or walk, which generally provide point-to-point trips. In particular for trips not starting at home, it is furthermore unknown, whether a bike was even available in the given situation. Given the arguments outlined above, including bike in the choice set appears to represent a stronger assumption than excluding it from the choice set. Therefore, it was assumed that for the situations in question, the choice set consisted of free-floating car-sharing, public transportation and walk. However, a reference model including bike as an alternative was estimated to allow a comparison of the two approaches. Observations in which other modes were chosen were therefore dropped.

The pooled data set contains revealed preference data only. Therefore, non-chosen alternatives had to be generated in order to allow estimating a multino-

[3]In addition, 73.2% of the free-floating car-sharing members do not even have a private car in their household [16].

mial logit model. To do so, each of the trips was routed using the GoogleMaps Directions API [19] for the three modes *car* (for car-sharing), *public transportation* and *walk*. The routing was conducted according to the shortest path given the respective historic traffic situation and public transport schedule. The results of the routing were then used as attributes for the three alternatives. Yet, to cover direct and one-way trips only, choice situations for which the routed travel time deviated by more than 50% from the reported travel time in the original data set were excluded. Moreover, trips starting or ending outside of the free-floating car-sharing service area were excluded from further analysis, given that in these cases, free-floating car-sharing is not an available alternative (as only one-way trips are considered). In total, 44 674 choice situations remain. In some of the remaining cases, a public transport alternative is not available (e.g. during night times). Table 3 presents the choice frequencies of the pooled data set. Given this overrepresentation of car-sharing in the choices, the model cannot be used for a prediction of mode shares. However, to confirm consistency of the estimates, the model was also estimated on a re-weighted data set, in which the weight of car-sharing observations was scaled down.

To determine the price of the free-floating car-sharing alternative, the routed travel time was multiplied with the current rental rate of 0.41 CHF/min. For public transportation, the fare was calculated based on the routed distance using the official distance-based fare for public transportation in Switzerland [30]. No concessions or fare reductions (season tickets or other subscription) were assumed. Given the high share of public transport subscriptions among free-floating members reported by earlier studies [16], this is a rather strong assumption. Yet, assuming a lower fare appears arbitrary given that it is unclear which subscription would have been available in the individual choice situations. Moreover, an amortization factor for the subscription would have to be added to any reduced fare.

For each trip start and end point, the local service level of public transportation as defined in the Swiss standard SN 640 290 was determined using data provided by the Cantons of Basel-Stadt and Basel-Land. As above, service levels for Germany and France were not available, they were therefore assigned the lowest category.[4]

Eventually, the positions of available free-floating car-sharing vehicles were reconstructed based on the transaction data in 5 min intervals. This way, for each of the trips in the data set, the city-wide distribution of available free-floating car-sharing vehicles was determined at the individual trip start time. Based on this, the distance of the trip start point to the closest available vehicle was calculated for the four cardinal directions. The average of the four cardinal directions was then used as a proxy for access distance to the free-floating vehicle. Given the generally good parking availability in Basel, parking search time was not considered.

Using the data as described above, the mode choice model has then been estimated as alternative-specific conditional logit model [31] with clustered standard errors (by person ID). For each case i, the utility function of this model can be expressed as

$$u_i = \mathbf{X}_i\beta + (\mathbf{z}_i\mathbf{A})' + \epsilon_i$$

where $\mathbf{X}$ is a $J \times p$ matrix (with J the number of alternatives and p the number of alternative-specific variables) and $\mathbf{z}$ is a $1 \times q$ vector capturing the case-specific variables. Hence, β is the $p \times 1$ vector of alternative-specific regression coefficients, while $\mathbf{A}$ is the $q \times J$ matrix of case-specific regression coefficients. The model was estimated using Stata SE 14.2 [32]. The variables used in the model are summarized in Table 4.

[4] This is uncritical also because the car-sharing service area does not extend to Germany and France (with the exception of the airport, which is not considered as part of the main service area in this research).

The nature of the data sets used for this mode choice analysis entails methodological limitations. Those limitations mainly arise, because in the vehicle data set, car-sharing is always the chosen alternative. Due to this structure, no decision model can be estimated based on the vehicle data set alone (all effects are captured by the constant, while other predictors cannot be identified). As a consequence, it was neither possible to estimate a scale parameter [33] to control for the different origin of the two (partial) data sets nor was it possible to take into account panel effects [34]. From a behavioral standpoint, the limitations mean that in this analysis, the differences both between the data sets and between the individual decision makers are assumed non-significant - an assumption, which can be motivated by the fact, that both data sets describe revealed preferences of the same group in the same city and that according to earlier research, the group of free-floating car-sharing members appears to be relatively homogeneous [16].

Table 3: Choice frequencies

Alternative	n	share
car-sharing	29 963	67.1%
public transportation	3 716	8.3%
bike	5 193	11.6%
walk	5 802	13.0%

5.2. Results

In a first step, the routing results were analyzed descriptively to get first insights in the situations in which free-floating car-sharing was used. As presented in Figure 4, with an median travel time of 8 min, free-floating car-sharing was more than twice as fast as public transportation (19 min) and also substantially faster than walk (34 min) in the instances it was actually chosen (vehicle data). The travel time differences are much less substantial for diary trips, where the median travel time of car-sharing (5 min) was not substantially faster than public transportation (9 min; walk: 14 min), but public transportation alternatives

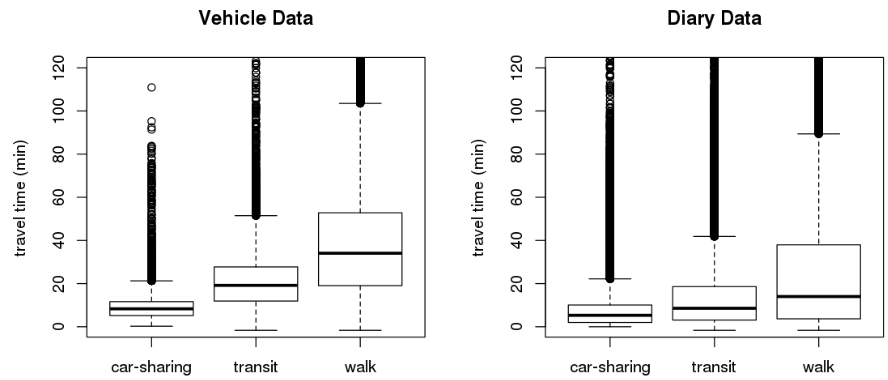

Figure 4: Distribution of travel times for the three modes (routed trips).

would have involved a median of 0.6 km access and/or egress walk for the vehicle data compared to 0.3 km in the diary data. No difference is observed in the average number of transfers of the public transport alternative.

The descriptive statistics outlined above already implies that the free-floating car-sharing scheme is mostly used for relations with inferior public transportation options. However, many other covariates may also play a role in the decision to use free-floating car-sharing. Therefore, a mode choice model as described above has been estimated to better understand free-floating car-sharing use.

The mode choice model is presented in Table 5. The left column presents the actual choice model (reduced choice set), whereas the right column shows the reference model (including bike as alternative). A Hausman-McFadden test [35] has been used to test the consistency of the two models. With a $\chi^2 = 122.44$ ($df = 20$, $p = 0.000$) it indicates that the IIA property does not apply for the bike alternative, i.e. excluding bike does have a significant effect on the estimates of the remaining parameters. Yet, with the exception of the parameters for travel time, none of the differences is substantial (c.f. Table 5). Hence, the following analysis is based on the mode choice model with the restricted choice set.

Due to its high correlation with cost ($\rho = 0.68$), tt_{car} could not be estimated efficiently. Yet, the results can give a first indication of the actual trade-offs taken for each trip. The model indicates a value of travel time savings (VTTS) of 16 CHF for public transportation and 33 CHF for walk[5], which is comparable to results from earlier studies in Switzerland [37]. Moreover, it is interesting to note that for walk towards or from a public transport stop, the VTTS is twice as high as for normal walk. Again, the value for access walk matches the results of earlier studies [37]. Therefore, the model is assumed to give a valid estimate of the actual elasticities.

A first result with respect to free-floating car-sharing is that access walk to a vehicle has a very low value of travel time savings (VTTS). Converting the parameter for $\text{d}_{\text{vehicles}}$ by a detour factor of $\sqrt{2}$ and a walk speed of $5\,\text{km/h}$ [38] yields $\beta = -0.668\,\text{h}^{-1}$ and thus a VTTS of less than 2 CHF/h - a value substantially lower than for public transportation. This indicates that car-sharing members are more willing to walk towards a car-sharing vehicle than towards a bus stop.

Yet, free-floating car-sharing has a lower alternative-specific constant than public transport. Thus, with all attributes being equal, public transportation is generally preferred over free-floating car-sharing. This holds particularly true for connections between areas with a high level of service of public transportation, for which the attractiveness of free-floating car-sharing is substantially reduced compared to public transportation.

[5] In the model for the extended choice set, the values are 10 CHF and 29 CHF. However, given the large confidence bands [36] of these elasticities, the differences are not significant.

From the case-specific variables, it can be seen that free-floating car-sharing becomes more attractive relative to public transportation during the night and when it is rainy and/or cold. In turn, it becomes less attractive for trips between areas which are frequently and densely served by public transportation. The walk alternative seems to be particularly attractive for (short) trips within a municipality.

Given the disproportionately high share of car-sharing observations in the data set, the estimates for the alternative specific constants are biased. It is therefore not possible to reliably predict a market potential of free-floating car-sharing. However, all other predictors in the model proved robust when re-weighting car-sharing observations and therefore provide a valid estimate of the respective elasticities.

Table 4: List of Attributes for mode choice model

Variable	Type	Description
cost	numeric	car-sharing rental fee / public transportation fare in CHF (zero for walk)
tt_{car}	numeric	car-sharing travel time in hours (zero for all other modes)
tt_{bike}	numeric	bike travel time in hours (zero for all other modes)
tt_{pt}	numeric	public transportation travel time in hours (zero for all other modes)
tt_{walk}	numeric	walk travel time in hours (zero for all other modes)
$d_{vehicles}$	numeric	average Haversine distance of closest available car-sharing vehicle by cardinal direction (zero for all other modes)
$t_{pt\text{-}walk}$	numeric	time of access/egress walk to/from public transportation in hours (zero for all other modes)
$t_{pt\text{-}wait}$	numeric	waiting time at the first public transport stop before commencing the ride in hours (zero for all other modes)
$n_{pt\text{-}transfers}$	numeric	number of transfers involved in the public transportation alternative (zero for all other modes)
high level of pt service	factor	both the start and the end point of the trip are situated in an area with the highest transit service level (level A)
mid level of pt service	factor	both the start and the end point of the trip are situated in an area with an acceptable level of transit service (level B or C)
inner-city trip	factor	origin and destination of the trip within the same municipality
night	factor	trip start between 10 pm and 6 am
rainy	factor	precipitation > 0 during the hour of the trip start
cold	factor	temperature $< 2°C$ during the hour of the trip start

Table 5: Mode choice model: multinomial logit model with alternative specific constants and clustered standard errors. Please refer to Table 4 for a description of the variables.

	reduced choice set			extended choice set		
	Coef.		z	Coef.		z
mode						
cost	-0.433	**	-2.06	-0.461	**	-2.20
tt_{car}	-8.027		-1.52	-2.881		-0.55
tt_{bike}				-12.732	***	-17.52
tt_{pt}	-6.843	***	-8.27	-4.822	***	-6.81
tt_{walk}	-14.542	***	-28.02	-13.338	***	-29.61
$d_{vehicles}$	-0.188	***	-2.83	-0.132	**	-2.21
$t_{pt\text{-}walk}$	-28.085	***	-24.87	-26.047	***	-24.69
$t_{pt\text{-}wait}$	-4.624	***	-9.43	-4.427	***	-9.52
$n_{pt\text{-}transfers}$	-0.764	***	-6.20	-0.812	***	-6.90
car-sharing						
high level of pt service	-1.248	***	-6.01	-1.159	***	-5.50
mid level of pt service	-0.357	*	-1.72	-0.283		-1.36
inner-city trip	-1.369	***	-3.40	-1.245	***	-3.17
night	-0.157		-1.52	-0.170	*	-1.73
rainy	0.699	***	5.26	0.673	***	5.20
cold	0.182	**	2.13	0.187	**	2.26
constant	2.009	***	3.97	1.733	***	3.59
bike						
high level of pt service				-0.046		-0.23
mid level of pt service				0.043		0.19
inner-city trip				-0.810	***	-3.73
night				-0.116		-1.02
rainy				-0.247	*	-1.67
cold				0.005		0.05
constant				-0.811	**	-2.56
public transport						
high level of pt service	-0.657	***	-3.05	-0.546	***	-2.62
mid level of pt service	-0.415	*	-1.72	-0.352		-1.52
inner-city trip	-1.149	***	-4.18	-1.108	***	-4.09
night	0.416	***	3.33	0.264	**	2.25
rainy	0.153		1.08	0.184		1.34
cold	0.190	**	1.87	0.171	*	1.75
constant	2.537	***	3.46	2.485	***	3.43
walk	(base alternative)			(base alternative)		
N	38 765			43 958		
null log pseudolikelihood	-32 853			-48 457		
log pseudolikelihood	-15 681			-30 974		
Wald χ^2	1 890	***		2 395	***	

*Significance codes: 0.10 * 0.05 ** 0.01 ****

6. Discussion

The results of the two models presented above can be combined with insights from earlier research to provide new perspectives on the drivers of free-floating car-sharing demand.

Beginning with the spatial analysis, this research has shown that in general, free-floating car-sharing activity scales with population density. This way, it complements findings from Berlin and Munich stating that demand scales with the size of the target population (aged 30-50 years) as well as the number of registered businesses in a given area [18]. Yet, in this research, the number of work places was found to have a negative effect on car-sharing activity.

A possible interpretation of this is, that free-floating car-sharing activity in general scales with social activity in a given area, whereas economic activity has a much lower - or even inverse - effect, which is in contrast to station-based car-sharing [11]. This implies that although opening up car-sharing for one-way and especially commute trips, free-floating car-sharing is still mostly used for discretionary trips.

Also the share of car-sharing members residing in an area was found to have a significant impact on the system's use, which confirms an assumption made in Schmöller et al. [18], that a substantial share of the free-floating car-sharing trips actually starts or ends at the members' homes. The results are similar to earlier research finding that station-based car-sharing activity scales with the number of members nearby [12].

Interestingly, free-floating car-sharing activity is higher in areas which see a lower overall car or public transportation mode share. A possible interpretation is that - depending on the situation - free-floating car-sharing is used as an alternative to both car and public transportation.

Moreover, according to the model outlined above, free-floating car-sharing is also used with disproportional intensity in areas with lower accessibility. This observation goes in line with findings from the mode choice model revealing that free-floating car-sharing is most attractive for tangential relations, which are not well served by public transportation. A possible interpretation is that free-floating car-sharing is used to bridge gaps in the public transportation network. In this aspect, it differs from station-based car-sharing, which was earlier found to thrive best in areas with low car-ownership levels and superior level of service of public transportation [9, 10].

The results also show that customers are willing to accept a substantially longer access walk to the car-sharing vehicle than for public transportation. Yet, the additional walk is usually made up for by a shorter overall travel time. However, an alternative interpretation would be that also the use cases may be different beyond the variables captured by the model. Eventually, as in the literature [18], adverse weather was found to fuel the demand for free-floating car-sharing.

Yet, there are various limitations in the two modeling approaches presented above, which should be considered when interpreting the results and which should be addressed in future research. For example, in the spatial regression model, it would be interesting to include departures from the airport. Moreover, the quality of the model would benefit from an enhanced measure of accessibility based on routed travel times in the network and from the inclusion of additional attributes such as gender distribution and household sizes, which were not available in this research.

Estimating the mode choice model on a pooled data set incurs several limitations. For example, given the lack of any individual information on the traveler or trip, it is not possible to account for the ownership of mobility tools or trip purposes when determining the individual choice set and attribute levels (reduced ticket prices for season ticket holders). Instead, in this analysis, the same (reduced) choice set was assumed for all individuals, which likely causes bias in the estimates [39]. Yet, all of the observations stem from the same group of members of the free-floating car-sharing scheme, which should reduce heterogeneity given that in earlier research, this group was found to be relatively homogeneous [16]. Moreover, a comparison of the two models presented in Table 5 indicates that their general behavioral interpretation is consistent.

The nature of the pooled data set (in the vehicle data, the car-sharing alternative is always chosen) entails further limitations on the methodological side in that neither the (possibly) different utility scale nor the obvious panel structure (and thus individual-specific effects) could be captured in the model. Although the underlying assumptions can be motivated by the fact that both the data sets and the decision makers are relatively homogeneous, this aspect deserves further investigation once better data becomes available.

In addition, the pooling of the data set comes with the drawback that car-sharing trips are over-represented in the sample. While this does not bias the estimates of the model parameters, it does affect the estimation of the alternative-specific constants, so that the model cannot be used to make any predictions (e.g. of potential demand levels of an area nearby).

A minor drawback of the mode choice model is that it only captures one-way trips. For future research, it would be worthwhile to study the nature of multi-stage trips in more detail. Moreover, the final prices for car-sharing use were assumed in the model. However, customers do not have perfect information on their exact travel time (especially during peak hours), so that unobserved factors (e.g. risk of delay and thus higher cost) may in fact also play a role. Moreover, psychological factors may have an effect on the choice, too. Yet, despite the limitations discussed above, it should be noted that the results of the mode choice model are in line with the results of earlier research as far as conventional modes are concerned. Hence, it can be assumed that the insights generated with respect to free-floating car-sharing generally are valid.

7. Conclusion

The results presented in this research contribute to a better understanding of the drivers of free-floating car-sharing demand. The results indicate that free-floating car-sharing is mainly used for discretionary trips, for which only substantially inferior public transportation alternatives are available.

Moreover, comparing the results to findings from earlier research indicates substantial differences in the use cases of free-floating and station-based car-sharing. Although both systems are mostly used for discretionary trips, station-based car-sharing relies on local public transportation access, whereas free-floating car-sharing bridges gaps in the public transportation network.

However, given various methodological limitations due to the nature of the available data, the results of the mode choice model have to be interpreted as a first attempt to study use cases of free-floating car-sharing in a quantitative way and should be re-evaluated once better data becomes available. In addition, only one-way trips could be covered in this research. Yet, there also is a substantial share of multi-stage trips conducted using free-floating car-sharing, which exhibit different usage patterns. A future analysis of those trips may yield further insights on the interoperability between station-based round-trip and free-floating car-sharing.

Nonetheless, the results of this research can already be used in microscopic transport simulation tools such as MATSim [40] to improve the representation of free-floating car-sharing. In particular, given the limited availability of empirical data about such schemes so far, applying the results of the mode choice model can help to improve the behavioral realism of of agent-based simulations. In turn, comparing the results of an agent-based model to the spatial regression results may provide an additional layer of validation.

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