DISS. ETH NO. 19-26081

THE ROLE OF SHARED MOBILITY IN AN INTEGRATED TRANSPORT SYSTEM

A thesis submitted to attain the degree of

DOCTOR OF SCIENCES of ETH ZURICH
(Dr. sc. ETH Zurich)

presented by

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2019

ABSTRACT

Shared mobility services such as car-sharing, bike-sharing or ride-hailing challenge the common categorization into private and public modes. Whilst often used in direct competition to public transport in the short term, they may allow its members to forego their private car in the long run. Although earlier research has confirmed that positive net impacts are generated by station-based car-sharing, these results are not necessarily transferable to the fast-evolving modes of free-floating car-sharing, bike-sharing or ride-hailing, which offer higher flexibility, but less predictable availability.

Hence, this thesis aims to study the travel behaviour impacts of more flexible modes of shared mobility and analyzes potential ways to most effectively integrate them into the existing transport system. To do so various data sets such as a national travel survey, dedicated car-sharing member surveys as well as original transaction data of a local operator are used. They were analyzed using various descriptive and econometric methods. In addition, simulation experiments using MATSim allowed a glimpse on possible paths of future development.

The results indicate that for car-sharing, customers of flexible services are different from members of the station-based counterparts. The services are also used in different ways, translating into lower (yet still positive) impacts on travel behaviour for free-floating car-sharing. Moreover, results show that free-floating car-sharing is often used as a substitute for unattractive public transport connections, thus bridging gaps in the network. Yet, on a system-level, potential impacts of shared modes seem limited, so that accompanying policy measures will be required to generate substantial benefits. In such a setup, shared modes would be part of an integrated transport service, along with public transport and potentially even private cars.

Insights generated by this research can be of interest to mobility operators as they provide detailed information on target groups, demand patterns and competition with other shared modes. In addition, policy makers can obtain a clearer picture of the respective system-level impacts and decide whether to actively manage or even support the different services.

ZUSAMMENFASSUNG

Angebote geteilter Mobilität wie zum Beispiel Car-Sharing, Bike-Sharing oder Ride-Hailing lassen sich nur schwer in die herkömmlichen Kategorien des öffentlichen Verkehrs oder des Individualverkehrs einordnen. Zwar werden sie zur Zeit oft als direkter Ersatz für Fahrten mit dem öffentlichen Verkehr genutzt; langfristig erlauben sie jedoch einem Teil ihrer Kunden den Verzicht auf ein privates Fahrzeug. Frühere Studien haben gezeigt, dass für das Stations-basierte Car-Sharing letztere Effekte überwiegen und sich positive Wirkungen auf das Verkehrssystem einstellen. Aufgrund der höheren Flexibilität und geringeren Verlässlichkeit lassen sich diese Erkenntnisse jedoch nicht unbedingt auf die schnell wachsenden Angebote des free-floating Car-Sharing, Bike-Sharing oder Ride-Hailing übertragen.

Ziel dieser Arbeit ist es daher, zu untersuchen, welche Wirkungen flexible Angebote geteilter Mobilität auf das individuelle Verkehrsverhalten haben und wie diese am besten in das bestehende Verkehrssystem einzubinden sind. Hierfür standen verschiedene Datensätze zur Verfügung: vom Mikrozensus Mobilität und Verkehr über eine eigens geführte Befragung von Car-Sharing-Mitgliedern bis hin zu Buchungsdaten eines lokalen Car-Sharing-Anbieters. Die Auswertung erfolgte mit deskriptiven sowie verschiedenen ökonometrischen Ansätzen. Zusätzlich wurden Simulationsexperimente in MATSim genutzt, um verschiedene langfristige Entwicklungspfade zu untersuchen.

Die Auswertungen zeigen, dass beim Car-Sharing deutliche Unterschiede zwischen den Kundengruppen der flexiblen und der Stations-basierten Angebote bestehen. Auch werden die Angebote auf unterschiedliche Weise genutzt, was auch zu anderen Wirkungen auf das jeweilige Verkehrsverhalten führt. Die positiven Externalitäten fallen beim flexiblen Car-Sharing geringer aus als beim Stations-basierten Car-Sharing. Zudem lässt sich erkennen, dass Free-floating Car-Sharing häufig als Ersatz für unattraktive Verbindungen beim öffentlichen Verkehr genutzt werden, und das Angebot dadurch ergänzen. Auf Ebene des Gesamtsystems sind die möglichen Wirkungen von Angeboten geteilter Mobilität jedoch begrenzt, sodass begleitende verkehrspolitische Massnahmen erforderlich sind, um einen grösseren Nutzen zu generieren. Angebote geteilter Mobilität wären dabei nur

ein Element integrierter Verkehrsangebote, die auch den öffentlichen Verkehr und womöglich sogar das private Automobil umfassten.

Die Erkenntnisse aus dieser Arbeit dienen sowohl Betreibern als auch Verkehrsplanern. Für erstere sind insbesondere die Einblicke in Zielgruppen, Nachfragemuster und zum Wettbewerb mit anderen Angeboten hilfreich, um ihre Dienste zu optimieren. Verkehrsplaner erhalten durch die Auswertungen ein klareres Bild von den Vor- und Nachteilen der verschiedenen Angebote und können so informiert entscheiden, inwieweit sie steuernd oder gar fördernd eingreifen sollten.

ACKNOWLEDGEMENTS

I am grateful to many for their advice, support and inspiration, that made this thesis possible. And while it is impossible to name them all in detail, there are a few persons whose efforts I would like to highlight.

Kay W. Axhausen and Francesco Ciari not only served as supervisors of my thesis. Even more importantly, they constantly encouraged me to go beyond existing research projects and develop new ideas, some of which have even led to successful student theses or independent research papers. I sincerely thank both of them for placing their faith in me by offering me this great opportunity to do research in transport planning, despite my limited prior experience in the field, and for guiding me through the past five years of my academic life.

Warm thanks are due also to Scott Le Vine, who has not missed any opportunity to provide constructive and well thought-out feedback to my papers and research ideas, even before he had been appointed as a co-supervisor.

Another ingredient of this thesis was the inspiring and pleasant atmosphere at the institute. I am indebted to various colleagues for the many inspiring discussions and the assistance I received for my choice modeling and MATSim work. Special thanks for their support go to Milos Balac, Felix Becker, Patrick Bösch, Sergio Guidon, Sebastian Hörl, and Allister Loder, who have also turned into friends and co-authors. In addition, I am thankful for the great technical support by Peter Lorch, who went far beyond his duties to provide the hardware and software infrastructures needed for my research.

This research would not have been possible without the generous financial support of the Swiss National Science Foundation. Special gratitude is also extended to the teams of Mobility Carsharing and Catch a Car for allowing me to conduct such an in-depth analysis of their services.

I could not have completed this thesis with the continuous and strong support by my family and friends, and in particular by my wife Anika. Thank you for everything!

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1

INTRODUCTION

The whole is greater than the sum of its parts.
— Aristotle

1.1 CONTEXT

Transportation is a derived demand. People usually do not live where they work and their discretionary activities lead them to yet other locations. When travelling between those places, travelers generally aim to minimize inconvenience (Axhausen and Gärling, 1992).[1]

For most of the 20th century, travelers could generally choose between two motorized modes of ground transportation: private car and public transportation. While the former offers both spatial and temporal flexibility, a substantial investment up-front is required (acquisition, taxes, insurance, etc.), after which a private car is available at relatively low marginal cost.[2] In contrast, understanding mobility as a basic need, public transport services provide access to an entire region at subsidized fares.[3] Also here, up-front investments into season-tickets are usually possible, which subsequently allow use of public transport services at zero marginal cost.

The cost structures outlined above constitute market barriers, splitting travel decisions into a strategic level (mobility tool ownership) and a tactical level (mode/route choice), which is however strongly influenced by the former (Le Vine, 2011), leading to sub-optimal outcomes. And even if choice was only on the tactical level, a hub-and-spoke network of public transport services could not offer the same flexibility as a private car: For example, in Switzerland, averaged over all municipalities, accessibility by public transport is 35 % lower than for private cars (Axhausen et al., 2011).

1 Inconvenience (or generalized cost) includes all aspects of a trip from monetary cost and travel time up to comfort (among other attributes).

2 Leasing arrangements have been developed to ease the financial burden of buying a car, but do not substantially alter the relationship of fixed and variable cost.

3 Note that initially, public transport services had been developed by private investors offering connections along major corridors (compare Day and Reed (1963)).

Making use of advances in digitization and information technologies, new modes have emerged, which challenge the traditional dualism of private and public modes. Most prominent examples are car-sharing, bike-sharing and ride-hailing.[4] While car-sharing allows to apportion the substantial fixed costs of car ownership among multiple users, bike-sharing and ride-hailing offer flexible and fast point-to-point connections. This way, all three services may complement public transportation offerings and may render private car-ownership less attractive.

In parallel to the emergence of shared modes, focus of urban transport planning has shifted away from the *predict and provide* approach towards more active demand management (Owens, 1995). This is based on the insight that adding further transportation infrastructures would not only be expensive, but would actually reduce economic attractiveness of the urban centers (Banister, 2002). In addition, reducing negative externalities such as (local) pollution and (global) energy consumption have become further goals of transport policy.

Given their potential to make public transport more attractive and to reduce the need for car-ownership, shared modes may be part of modern transport policy, especially with their systems' steady growth. In turn, most shared modes depend on public support because they require access to on-street parking, sidewalks or curb space to offer their services.[5]

And although many operators of shared modes claim to generate positive externalities to the transport system, reductions in car-ownership or energy consumption have been empirically confirmed only for station-based car-sharing (Cervero et al., 2007; Martin and Shaheen, 2011b), which provides reservation-based access to vehicles at pre-defined locations (usually for round-trip use). However, recent growth rates have been substantially higher for the more flexible forms of free-floating car- or bike-sharing as well as ride-hailing, which all offer flexible point-to-point connections (Shaheen et al., 2015). Given the different nature of these systems, it is all but

4 Car-sharing and bike-sharing offer customers short-term access to a fleet of vehicles. In addition to usage-dependent fees, some service may charge membership fees. Ride-hailing offers chauffeur-driven point-to-point rides and usually charges per trip (fare may vary depending on demand). More detailed descriptions are provided in Chapter 2.

5 In reality, many such schemes simply exploit such public spaces without obtaining permission by local authorities.

clear if insights on usage patterns and travel behaviour impacts will be the same as for station-based car-sharing.

Up to this date, fleets of shared modes have been relatively small (at least in the European context) and have usually operated separately from each other, and from public transportation. However, network effects could likely be seized, with a mutual reinforcement of supply and demand, which may even affect demand characteristics (Ciari et al., 2014). Moreover, an integration with public transport (with respect to operations and/or ticketing) may help to increase public transport coverage in lower-density areas (by providing options for first/last mile connections or tangential trips). Potentially, shared modes could even become a cornerstone of fully-integrated *Mobility as a Service (MaaS)* offerings (Mulley, 2017).

1.2 CONTRIBUTIONS

As part of this thesis, a wide range of analyses were conducted to better understand the current role of shared mobility and its potential impacts on the system-level. There was a primary focus on free-floating car-sharing, since it was the most promising mode at the time of this research and its counterpart, station-based car-sharing, had already been well researched. However, some of the results may also be transferable to other shared modes.

In a first step, a new multivariate probit model for mobility tool ownership was estimated for the Swiss national household travel survey (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012) to study, how station-based car-sharing membership is combined with other mobility tools (i.e. car ownership and public transport subscriptions). The results allow a first glimpse at possible substitution patterns.

Thereafter, survey data was used to study differences in customer groups and usage patterns between station-based car-sharing and free-floating car-sharing. While the former had already been well established in Switzerland, the latter was a younger, but fast-growing service. The results helped to determine each service's use cases as well as market potential. Such information can be used to identify candidate cities for future car-sharing operations.

Thirdly, panel data collected in the same survey as above was used to measure the impact of free-floating car-sharing on private vehicle holdings. The impact was determined using a treatment-effect model. It represents a novel approach to measure the car-ownership impact of free-floating car-sharing based on empirical data. This way, it went beyond earlier research, which mostly relied on respondents' retrospective self-assessment.

To shed further light on the use cases of free-floating car-sharing, a mode choice model was estimated based on a pooled data set of car-sharing rentals and travel diaries. The results help to understand, in which situations free-floating car-sharing is used and how it competes with public transportation. In addition, a spatial regression approach provided insights on the long-term drivers of car-sharing demand, which help to better design service areas.

The empirical data used in the research pieces above helped to gain relevant insights into usage patterns and impacts of a current free-floating car-sharing scheme. However, most schemes of shared mobility in Switzerland still operate with very limited fleet sizes. Yet, it can be expected that due to network effects, usage and impacts may be different for large-scale fleets. To test this assumption and also to determine system-optimal fleet sizes, MATSim simulations were carried out. To the author's best knowledge, this also marks the first time that free-floating car-sharing, free-floating bike-sharing and ride-hailing were simulated jointly in MATSim. Most importantly, the results allow insights on a possible integration of shared modes with public transportation.

1.3 OUTLINE OF THESIS

This cumulative thesis is structured as follows: There are seven main chapters presenting a focused summary of the research conducted in this thesis. The main chapters are followed by pre-prints of the five individual papers in the appendix, which provide a more in-depth discussion of the respective methods and results.

In the remainder of the main part, Chapter 2 presents the theoretical and practical backgrounds of this work, with a focus on the two dimensions of mobility tool ownership and mode choice as well as earlier work on shared mobility. In Chapters 3 and 4 the methodologies and data are introduced, along with a discussion of potential alternatives. Chapter 5 then provides summaries of the five research papers of this thesis. The relevance of the findings in research and practise is discussed in Chapter 6. Finally, Chapter 7 concludes the thesis with suggestions for policies and business models as well as potential avenues of future research.

2 BACKGROUND

Just as one must not receive, so must one not possess anything which one does not really need.
— Gandhi

2.1 MOBILITY TOOLS AND MODE CHOICE

Vast amounts of research have been conducted to study travellers' mode choice preferences (Stopher, 1969; McFadden, 1974a; Cervero, 2002; Buehler, 2011). Independent of the specific methodology, data sources and local context, there has been agreement that travel time[1], cost, comfort and reliability are the key determinants of mode choice (Vrtic et al., 2003).

From the above list, only travel time can be measured objectively. Comfort and reliability are likely to be perceived differently by travellers, but abstract scales as well as random-parameter models can be used to address this issue (Hensher and Greene, 2003). The cost attribute is more problematic as it is often unclear, which costs travellers actually consider in their decision. In SP-settings, normally the out-of-pocket costs are used. For public transport services, this is the fare paid for the trip, while for cars fuel costs are considered the decision-relevant attribute. Hence, both cost values are strongly affected by the mobility tools owned by the traveller.

Table 2.1 illustrates this issue by presenting the different cost levels for public transport and car for a trip from the city center of Zurich to the city center of Bern (120 km; about 80 min by public transport, 15 min longer by car). As can be seen in the table, owning a public transport season ticket or disregarding sunk cost of car ownership substantially changes the cost for the trip. A comparison with values of travel time savings (32 CHF/h for car and 20 CHF/h for public transport (Hess et al., 2008)) shows that these differences are decisive. As a result, travellers are often captive to the mobility tools they own, resulting in possibly sub-optimal choices (also

1 In the context of public transportation, also access/egress time, headway and number of transfers play an important role.

Mode	Mobility tool / Cost component	Amount [CHF]
Public transport	full cost	51.00
	Halbtax (185 CHF/year)	25.50
	GA (3 860 CHF/year)	0.00
Car	full cost	59.65
	only variable cost	23.12
	only fuel cost	6.90

TABLE 2.1: Cost per passenger for a trip from Zurich to Bern for different modes and mobility tools. Public transport fares from `www.sbb.ch` for 2nd class; car costs according to Bösch et al. (2018) (based on usage of 15 000 km per year).

compare Le Vine (2011)). Shared modes and flexible public transport services may help to overcome this dualism.

Another recent idea to overcome market segmentation by mobility tool ownership is the concept of *Mobility as a Service (MaaS)* (Mulley, 2017). Key elements of this concept are an integrated strategic and operational planning (including network design and fare integration) of all transport modes as well as an integrated user interface through which trips can be planned and booked (Kamargianni et al., 2016; Jittrapirom et al., 2017). Most revolutionary, also (private) cars would be part of this system. Concerning ticketing, two different approaches are envisioned: either travelers (*mobility consumers*) purchase packages of monthly usage credit for the different mobility services (Sochor et al., 2016) or they will be charged per trip (pay as you go). In a way, the first approach would remove any cost (and thus efficiency) considerations from mode choice decisions (as marginal costs are removed from the equation), while the latter approach would clearly allow the most informed trip-level decisions.

2.2 THE ROLE OF PUBLIC TRANSPORTATION

Early forms of urban public transport services were established in the 19th century with ferries, horse-drawn omnibuses as well as the first subway and commuter rail lines. Planning, construction and operations were usually all done by private investors at their sole risk (Day and Reed, 1963; Cudahy, 1995). Economic interests of the individual operators in combination with a distinct lack of regulation often led to wasteful competition on major corridors, at the expense of low accessibility of areas with lower demand or purchasing power. Notable exceptions are the Moscow metro, which had been planned and operated by public authorities from the very beginning, as well as the Berlin underground, which had been constructed and operated by private companies under a license granted by the city's transportation authorities.

Especially in the United States, fierce competition and the great depression drove most private operators out of business. Public authorities subsequently took over control of operations and introduced an integrated planning for different modes of public transportation (such as buses, metro and commuter rail). Public transportation became even more tightly regulated; often private companies could only operate with official permission (Day and Reed, 1963; Cudahy, 1995).

The change in ownership also came with a change in primary objectives. Understanding mobility as a basic need, the new primary goal of public transportation has been to provide a solid level of accessibility throughout a city or region. Generating profits was not a priority anymore. Instead, fares are set politically to ensure rides are affordable to everyone; financial losses are balanced by public subsidies. With public transport ensuring equity in access, focus of transport planning in the mid-20th century was to provide road networks for the growing demand for car travel (Banister, 2002).

However, becoming aware of the substantial negative externalities of private car travel (such as space and energy consumption, pollution and noise), more and more authorities have aimed to promote alternatives to private cars in the past decades. Consequently, public transport networks and cycling infrastructure have been substantially extended in European cities.[2] In addition to equity, reductions of overall energy consumption and pollution have become major goals of (public) transport planning.[3]

2 Examples are the metro (S-Bahn) concept in the greater Zurich area as well as the large-scale expansion of cycling infrastructure in Copenhagen.

3 In addition, Zurich aims to limit space consumed by transportation infrastructure by limiting parking spaces and downgrading arterial roads.

2.3 SHARED MOBILITY

In the past two decades, advances in digitization triggered the rise of shared mobility. A common definition of shared modes is that they provide their members access to vehicles for short-term use against a usage-dependent fee.[4] Although early forms of car-sharing and bike-sharing date back to the 1940s, new information technologies allowed them to counter vandalism and reduce transaction costs and thus become attractive to the broader public (Millard-Ball et al., 2005; Parkes et al., 2013; Shaheen and Cohen, 2013). Most schemes were station-based: vehicles were available for pick-up from designated stations and had to be brought back to such a station at the end of the rental. Car-sharing vehicles often have to be returned to the origin (round-trip rentals), while most bike-sharing operators allow one-way rentals. Another difference is that station-based car-sharing rentals require advance reservations including the return time/date, while advance reservation is usually not possible for bike-sharing. And lastly, station-based car-sharing operations were often launched by cooperatives or companies and were profitable, most bike-sharing schemes relied on subsidies or sponsors.[5]

Technological advances did not only help existing schemes to smoothen their services, but also sparked new business models. For example, free-floating schemes disrupted the car-sharing and bike-sharing market. In such schemes, available vehicles can be located using a smartphone-app. They can be used for one-way rentals within a pre-defined (city-wide) service area. At the end of the rental, they can be dropped off at public on-street parking spaces or on sidewalks (for bikes). The free-floating model provides substantially more flexibility to users than station-based services, but cannot offer comparable reliability (e.g. advance reservations longer than 15 min are either not possible or chargeable). While fleet sizes and customer base of free-floating car-sharing schemes have quickly outgrown station-based car-sharing in Europe, the trend for bike-sharing is less clear

4 The key difference to conventional car or bicycle rental companies is that reservations are done for (half-)hourly increments instead of days. Also, fuel is often included in the rental fee.

5 Initially, many bike-sharing schemes were operated by advertisement brokers in return for exclusive access to public ad spaces (Parkes et al., 2013).

(Shaheen et al., 2018). Also, free-floating operators rarely reveal any business numbers so that their profitability remains unclear.

Electric propulsion opens up further possibilities for shared mobility operators. As they are often used for short intra-urban trips, range limitations of electric vehicles do not lower their attractiveness. Moreover, electric vehicles may help to further reduce the ecological footprint of car-sharing services,[6] while electric bicycles level the perceived burden of gradients. Yet, in both cases, vehicle-charging adds to the operational complexity of free-floating schemes.

In the past years, other forms of shared mobility have been introduced, such as electric scooters or shared motorbikes. To reduce complexity of this research, they were abstracted into electric bicycles, but in case of further growth, they may be an interesting topic of future research in their own right.

Ride-hailing (or ride-sourcing) has initially also been framed as shared mode, although it is much closer to taxis or other chauffeur-driven services. Ride-hailing customers order a vehicle via a smartphone app. The system will then match an available vehicle and dispatch it to pick up the customer and drive him to the given destination. Fares consist of a base fare as well as time- and distance-dependent components and are adjusted to demand. Other features are in-app payments (no cash involved) as well as mutual reviews. In addition to point-to-point services, ride-hailing companies have launched pooled services, where travelers share the vehicle with other clients for parts of their journey for a discount on the individual fare.[7]

Shared modes challenge the traditional division of motorized modes into private cars and public transport. On one hand, they provide affordable point-to-point connections without the need of owning a mobility tool. On the other hand, operators can adjust fares and service levels at their sole discretion and mostly concentrate on higher-density areas, which offer the highest demand.

6 The net impact also depends on the energy source used for electricity generation.

7 Other services offering pooled rides or dynamic on-demand transit exist, but are not covered in this research.

2.4 SHARED MOBILITY IN SWITZERLAND

Switzerland has been the birthplace of station-based car-sharing (Shaheen and Cohen, 2013). Moreover, the generally high willingness to pay for services combined with a strong public transport system also invited various other shared mobility operators to launch their services in the country, particularly in the past few years.

Early implementations of station-based car-sharing date back to 1948, when the *Sefage (Selbstfahrergenossenschaft)* scheme was launched in Zurich (Harms and Truffer, 1998). Yet, ever-cheaper availability of private cars soon limited the demand for such a service. Modern car-sharing dates back to operators founded in the late 1980s. Merged in 1997, *ShareCom* and *ATG* have become a large-scale system offering access to about 3 000 shared vehicles at 1 500 stations covering the whole country. The new brand name is *Mobility Carsharing*.[8] This is different from most other schemes internationally, which usually focus on centers of larger cities. As the currently largest operator of shared mobility in Switzerland, it has more than 130 000 customers (about 2.5 % of all driving license holders).

Free-floating car-sharing has been launched in Switzerland in 2014. The service is currently available in Basel (150 vehicles) and Geneva (100 vehicles).[9] Since on-street parking is strictly regulated in Swiss cities, further expansion of such services strongly depends on their political support.

Station-based bike-sharing has been available in a number of cities since 2009. Yet, the hilly topography and a lack of cycling infrastructure have prevented a major uptake. Electric bikes and extensions of the infrastructure have triggered new growth. Addressing the same market, other operators have launched free-floating bike-sharing schemes, some also with electric bikes. In total, more than 7 000 shared bikes were expected to be operational by 2019.[10] Until now, only around half of this supply has been realized since some operators withdrew from the city or declared bankruptcy. The void was filled by yet other operators, offering smaller fleets of shared electric scooters or electric motorbikes.

8 The operator claims to serve every municipality with more than 10 000 inhabitants (`https://www.mobility.ch/de/mobility-genossenschaft/geschichte/`).

9 `https://www.catch-a-car.ch/en/home/`

10 `https://www.nzz.ch/zuerich/aktuell/o-bike-smide-und-co-mietvelos-ueberrollen-die-stadt-zue` `1311914`

Uber is the only ride-hailing service currently active in Switzerland. Its services are available in four of the five largest cities in the country (Basel, Geneva, Lausanne and Zurich). As of 2018, it claimed to have about 2 600 active drivers serving 300 000 customers annually.[11]

2.5 EARLIER RESEARCH ON SHARED MOBILITY

Research on shared modes has followed the different systems' popularity and data availability. In all cases, major research questions were the system-level impacts of shared modes as well as usage patterns and market potential. Given that bike-sharing operations were mostly subsidized, trip-level data was more easily available than for car-sharing or ride-hailing schemes, which were usually very hesitant to release any trip-level data.[12] Moreover, the whole market around shared mobility has been evolving at fast pace, rendering earlier research outdated very quickly.

The following subsections provide a brief overview of earlier research on the usage patterns and impacts of shared modes. More comprehensive reviews of the literature are presented by Shaheen and Cohen (2013) and Jorge and Correia (2013) for car-sharing as well as Fishman et al. (2013) and Fishman (2016) for bike-sharing. There is also a large stream of literature dealing with rebalancing methods and other optimization of shared modes, which is, however, beyond the scope of this research.

2.5.1 *User groups and usage patterns*

An important step in determining the market potential of shared modes is to understand their user groups and usage patterns. Member surveys as well as trip-level transaction data were generally used for this purpose.

Station-based car-sharing is the most well-researched shared mode so far. Various surveys across the globe found unanimously that car-sharing members were highly-educated young adults who live in small households (Burkhardt and Millard-Ball, 2006; Shaheen et al., 2006). In addition, dense

11 `https://www.blick.ch/news/wirtschaft/der-uber-schweiz-chef-im-grossen-interview-ja-wir-haben-fehler-gemacht-id8617739.html`

12 A notable exception is the nonprofit *Ride Austin* scheme, which released a comprehensive set of trip-level information.

urban areas with solid local public transport accessibility and low vehicle ownership rates were found to provide the most promising environment for car-sharing operations (Celsor and Millard-Ball, 2007; Stillwater et al., 2009). In fact, station-based car-sharing is perceived as an alternative to car ownership and hence it is most attractive for urban residents who travel only few kilometers with their private car per year (Litman, 2000). Using such insights, market potential of car-sharing schemes was estimated to about 10 % of the driving population (Steininger et al., 1996b; Muheim and Reinhardt, 1999; Shaheen et al., 2006). Yet, even in Switzerland with a nation-wide coverage, station-based car-sharing has not reached more than 2.5 % of all licensed drivers.[13]

However, given it has such a well-established car-sharing scheme and car-sharing membership has been captured by the national household travel survey since 2005 (Swiss Federal Statistical Office (BFS), 2006), Switzerland has often been used as a case study location to analyze factors influencing car-sharing membership. Ciari et al. (2015b) presented a first such attempt by applying a binomial model to study car-sharing membership as a function of socio-demographic characteristics. However they did not adapt the model to the low occurrence rates of car-sharing membership, potentially resulting in biased parameter estimates. A more recent work by Juschten et al. (2017) goes beyond this approach by also including individual attitudes towards transport policies and features of car-sharing supply. They suggest that also in Switzerland, highly educated males with higher incomes living close to car-sharing stations are more likely to become car-sharing members. Moreover, the availability of luxury cars at a nearby car-sharing station increases attractiveness of membership.

Scientific literature on one-way car-sharing and in particular free-floating car-sharing was much less abundant at the time of this research. Similar to station-based car-sharing, early studies found members to be younger residents of dense urban neighborhoods living in smaller households (Schmöller et al., 2015). Also, members show a more multi-modal travel behaviour (Kopp et al., 2015) and use car-sharing more often on rainy days (Schmöller et al., 2015). Other drivers of demand are population density, distance to city center, higher rents and density of hotels and restaurants (Seign et al., 2015). Given its higher flexibility, free-floating services were widely

13 compare business reports of *Mobility Carsharing*: `https://www.mobility.ch/en/mobility-cooperative/company-reports/`

thought to attract even more users to car-sharing (Shaheen et al., 2015).

For station-based bike-sharing[14], survey data revealed that members are relatively young, male, and highly educated as well as having an above-average income (Fishman et al., 2014b, 2015). Moreover, proximity to a bike-share station was identified as a key driver of demand (Bachand-Marleau et al., 2012). Convenience is the main reason to use bike-sharing (Shaheen et al., 2013), however, most members are infrequent users (Fishman et al., 2014b). In fact, more recent research indicates that bike-sharing is used by different user types, which each show very specific demand patterns (Buck et al., 2013; Faghih-Imani and Eluru, 2018). Curiously, hardly any research has used the above insights to estimate the market potential (in terms of members or mode share) for bike-sharing schemes.

Insights on ride-hailing are even more sparse in the literature. In one of the few early studies Rayle et al. (2016) report that the service attracts a broader user group than taxis and offers shorter wait times. Moreover, trip origins and destinations cover broader parts of the city, however with a clear focus on densely populated areas as well as business and nightlife districts.

While substantial research has been conducted to study user groups and typical trip patterns conducted with shared modes, only very recently a first quantitative analysis of mode choice behaviour has been presented (Li and Kamargianni, 2018). Such analysis is required as a base for even better predictions of the system's market potential and optimal service areas, for example through simulation experiments.

2.5.2 *Travel behaviour impacts*

Most researchers used member surveys to determine the impact of (station-based) car-sharing membership on their private vehicle holdings and mode use. In a common setting, members stated their level of car-ownership and use both for the present and retrospectively for a time before their membership. An alternative approach did not include retrospective questions, but asked directly for the change in behaviour, members attribute to their car-sharing membership. Both approaches involve various forms of response

14 Research on free-floating bike-sharing schemes had not been available at the time of this research.

bias. Nevertheless, the results have long shaped policy discussions on car-sharing. In particular, it was found that station-based car-sharing memberships reduce private vehicle holdings by 40-49 % (Meijkamp, 1998; Martin et al., 2010), translating into 9-23 replaced private vehicles per car-sharing vehicle (Martin et al., 2010; Stasko et al., 2013; Lane, 2005).

Vehicle kilometers travelled (VKT) and energy consumption were used as relevant indicators for behavioural change. Changes in energy consumption go beyond VKT, because it also accounts for the higher fuel efficiency of the car-sharing fleet (Rydén and Morin, 2005).[15] Survey results suggest average decreases in VKT of 30-50 % (Muheim and Reinhardt, 1999; Rydén and Morin, 2005; Martin and Shaheen, 2011a), with slightly higher reduction values for energy consumption.

Cervero and Tsai (2004) and Cervero et al. (2007) presented one of the rare attempts to address response bias by employing a panel-survey including a control group. Their results do confirm a substantial reduction in car-ownership (about 30 %). Car-sharing impacts on VKT also appear to be negative (reduction), but effects were not statistically significant.

To the author's best knowledge, no empirical analyses of free-floating car-sharing impacts have been available at the time of this research. In the literature, only a survey based on hypothetical scenarios had been presented. Using such data Firnkorn and Müller (2011) predicted substantial reductions of carbon emissions due to a first free-floating car-sharing scheme in Ulm, Germany. Yet, potential sampling bias and response bias may limit the validity of the results. An early empirical analysis by the Seattle Department of Transportation (2014) suggested that a large group of car-free members will slightly increase their VKT, while prior car holders may substantially reduce their VKT. Due to the limited scope of the survey, a net effect could not be determined. Also authorities from Amsterdam, The Netherlands, were unable to measure the impacts of free-floating car-sharing, because the fleet size was too small to produce a measurable effect (Suiker and van den Elshout, 2013).

Since riding a bicycle does not consume energy, the discussion on system-level impacts of bike-sharing schemes was distinctly quieter. However, ear-

15 Usually, car-sharing vehicles are younger, smaller and equipped with smaller engines than average private vehicles.

lier research has provided interesting insights. For example, Raux et al. (2017) found that a substantial amount of bike-sharing trips in Lyon, France, is used for first/last mile connections to public transportation. However, bike-sharing generally appears to substitute trips by public transport or active modes rather than car trips (Martin and Shaheen, 2014). Depending on the local context, this low replacement rate of car trips along with (motorized) relocation activities, required to balance supply, may even lead to an increase in overall energy consumption (Fishman et al., 2014a). This effect weighs even more heavily given that bike-sharing also does not appear to increase the general level of cycling, unless accompanied by upgrades in cycling infrastructure (Ricci, 2015).

Given the low data availability, research on the impacts of ride-hailing has been scarce so far. However, the few available studies clearly indicate a substantial increase in VKT. Using a user survey, Rayle et al. (2016) find that about half of all ride-hailing trips substitute a non-car mode. Taking into account vehicle occupancies and deadheading, a more recent study finds that ride-hailing users in Denver increased their VKT by 83 % (Henao and Marshall, 2018). Concerning the impact on vehicle ownership, no reliable information is available at this point.

2.6 RESEARCH QUESTIONS

As outlined above, the positive image of shared modes has mostly been shaped by insights on *station-based* car-sharing. However, in the past years, more flexible *free-floating* car- and bike-sharing services as well as ride-hailing have become even more relevant modes (based on customer growth and fleet sizes). Hence, the first main research question is to **determine the impact of such more flexible shared modes on the transport system**. This includes assessment of their customer potential as well as identification of typical usage and substitution pattern. Given that shared modes hardly fit into the dualism of public and private modes, the second main research question is **how to best integrate shared modes into the transport system** (w.r.t. system performance or total energy consumption). This includes a deeper analysis of mobility tool ownership patterns as well as simulation-based analysis of different forms of shared modes at large scale in the existing transport system.

3

METHODOLOGY

All models are wrong, but some are useful.
— George Box

3.1 MOBILITY TOOL OWNERSHIP MODELLING

From early on, there were attempts to include mobility tool ownership status in (trip-level) mode choice analysis (Train, 1980). However, it was only later that dedicated models for mobility tool ownership were developed. Following the fashion of transport planning, first approaches mostly focused on modeling the number and/or type of private cars in a household (de Jong et al., 2004).[1] In addition, joint models of vehicle ownership and use were proposed (De Jong, 1990; Bhat and Sen, 2006). More recently, Eluru et al. (2010) even present a framework to jointly model residential location choice, car ownership and car use. This integrated approach acknowledges that people may even self-select into certain neighborhoods based on their preferences for specific mobility tools (Loder and Axhausen, 2018).

Yet, in many European and Asian countries, the situation is more complex, because travelers can choose from a larger set of widely-used mobility tools, such as public transport subscriptions or motorcycles (instead of car ownership as the only relevant option). Scott and Axhausen (2006) showed that there are relevant substitution patterns between the different mobility tools (in their case between private car ownership and season ticket holdings).

To capture the inter-dependencies of the different mobility tools, Kowald et al. (2017) included season ticket holdings as explanatory variables for car ownership and vice versa. However, the mobility tools were still modeled separately, so that unobserved factors or endogeneity effects cannot be accounted for. This is also in contrast to the general observation that house-

1 Other approaches included cohort analysis to determine changes of car-ownership during the life-course as well as transaction models (de Jong et al., 2004; de Jong and Kitamura, 2009).

holds generally acquire portfolios of mobility tools instead of taking separate decisions (Simma and Axhausen, 2001). Such issues can be addressed by multivariate modeling approaches, where the different outcomes are modeled simultaneously (Greene, 2012). Examples are a bi-variate ordered probit model on car-ownership and season ticket holdings in Switzerland (Scott and Axhausen, 2006) or a tri-variate probit model on car, bicycle and motorbike ownership in Japan and Malaysia (Yamamoto, 2009). Until now, membership in any shared mobility scheme has not been analyzed in the context of individual mobility tool portfolios, yet.

Application in this thesis

In this research, a multivariate Probit model with sample selection was used to jointly study car ownership, holdings of two types of public transport passes as well as car-sharing membership (Becker et al., 2017c). Explanatory variables were socio-demographic attributes, individual transport policy attitudes and spatial characteristics of home and work location. Inter-dependencies between the choices are captured by correlation in the error terms of the individual model equation.

The selected methodology is substantially different from an earlier approach by Kowald et al. (2017), which is based on the same data. In their approach, an individual univariate Logit models were estimated for each of the four mobility tools. Inter-dependencies between modes are explicitly included by using the reported daily travel times by car and public transport as explanatory variables. Given that these variables are endogenous to mobility tool ownership, including them as predictors may bias the model results. However, Kowald et al. (2017) also explicitly model ownership of a driving license (although not combining it with car ownership in a two-stage approach (Heckman, 1979)). For simplicity, this was neglected in Becker et al. (2017c). Instead, the multivariate model was estimated twice - first for all observations and second only for driving licence holders.

3.2 MODE CHOICE MODELLING

Studying people's preferences in travel mode choices was an early application of discrete choice models (Ben-Akiva and Lerman, 1985; Train, 1986). Such models allowed to predict aggregate mode shares in a four-step-model (Ortuzar and Willumsen, 1990), but also to estimate values of travel time savings and other elasticities (Cherlow, 1981). Also in modern agent-based transport simulation tools, agents' decisions are often based on choice models (Hörl et al., 2018a).

Departing from the *multinomial logit or probit model (MNL / MNP)* various extensions have been developed to address its shortcomings or broaden its applications. Examples are nested approaches to overcome the IIA property of the MNL model (Daly, 1987) or mixed logit models to account for random taste heterogeneity (Hensher and Greene, 2003). More complex approaches include multi-variate approaches (see above) or hybrid choice models, in which latent attitudes are used as predictors for preferences (Ben-Akiva et al., 2002). While most approaches follow the underlying behavioural assumption of *utility maximization*, alternative formulations, e.g. *regret minimization*, have also been proposed (Chorus et al., 2008).

Many recent analyses rely on *stated preference (SP)* data, in which respondents can choose their preferred option(s) from a set of alternatives presented in their questionnaire. An alternative way to study mode choice preferences is through *revealed preference (RP)* data, in which respondents' actual choices were observed, along with all attributes of chosen and non-chosen alternatives (Louviere et al., 2000). While SP-methods often suffer from response-bias (Fifer et al., 2014; Hainmueller et al., 2015), RP-approaches may fail to accurately replicate the consideration set (Swait and Ben Akiva, 1987). There has been a long debate on the benefits and shortcomings of the two approaches, which is not reproduced here. In consequence, approaches to combine RP and SP data in model estimation have been developed (Ben-Akiva et al., 1994).[2]

A general limitation of discrete choice models is that they require the exact model specification as input, which may however result in parameter bias (especially for complex models). As an alternative, machine learning approaches allow simultaneous estimation of model structure and param-

2 Obviously, pooled estimation is not possible if future scenarios are to be studied.

eters (Goodfellow et al., 2016), but results are usually difficult to interpret.

In the context of shared mobility, conventional mode choice models have two further limitations: The first limitation pertains to the large set of different options (different shared mobility schemes plus conventional modes). In RP data, it is usually unclear, which options were actually considered by the traveller (Swait and Ben Akiva, 1987), whereas in SP experiments, users may not be familiar with all modes presented to them. Both mechanisms may bias parameter estimates and hence their interpretation.

The second limitation pertains to the *discrete* nature of the choice outcome, whereas in fact, shared modes are sometimes intended to be used as first/last-mile services. The multi-dimensional choice set makes it difficult to capture such inter-modal trips with the above methods. In principle, a *recursive logit* approach can be used to study such trips (Fosgerau et al., 2013) as it considers any feasible (inter-modal) path in a given network as a candidate route. Yet, *recursive logit* analyses would require high-resolution GPS traces and (multi-modal) transportation network data, which may not always be available. Meyer de Freitas et al. (2019) presented a first application for inter-modal trips in Switzerland. Including shared modes would add even further complexity to the problem.

Given these substantial challenges, attempts to include shared mobility in mode choice models are rare in the literature. And while the models by both Eiro and Martinez (2014) and Li and Kamargianni (2018) provide insightful results, both address the mode choice problem on a trip level, thus disregarding any inter-modal options.

Application in this thesis

In this research, Becker et al. (2017b) presents an attempt to estimate a mode choice model from car-sharing transaction data. The model aims to understand, in which situations free-floating car-sharing is usually used. As the transaction data had to be pooled with travel diary data to allow model estimation, alternative-specific constants may be biased. However, it can provide the effects of the different predictors (i.e. spatial characteristics of origin and destination, time of day, travel time and weather) as well as their elasticities.

Schmöller et al. (2015) also analyzed car-sharing transaction data, but used a clustering-approach to identify drivers of car-sharing demand. This way, they could identify spatio-temporal demand patterns. Moreover, a cross-table visualized the effect of time of day and weather. Hence, their approach allows a more in-depth analysis of the relationship between certain attributes and car-sharing demand, but it does not allow to quantify the actual effect size for the individual variables. However, both approaches (Schmöller et al., 2015; Becker et al., 2017b) do not allow prediction of mode shares.

3.3 SPATIAL DEMAND MODELING

In the literature, two approaches have been used to identify drivers of car-sharing demand. The first approach is to study socio-demographic characteristics of car-sharing users as well as their home locations and compare this with the general population (Steininger et al., 1996b; Burkhardt and Millard-Ball, 2006). In a second approach, *geographical information system (GIS)* information is used to explain car-sharing rental activity at certain stations or within aggregated zones (Stillwater et al., 2009; Schmöller et al., 2015). The two methods complement each other: Knowing drivers of membership allows to better target marketing campaigns, whereas understanding the drivers of demand (for rentals) helps to allocate vehicles and design service areas.

While modeling car-sharing membership usually is a simple application of a binomial logit or probit model, a spatial analysis of GIS data is methodically more complex. Although earlier approaches were able to identify certain spatial drivers of demand, they relied on simple linear regression approaches (Stillwater et al., 2009; Kortum and Machemehl, 2012; Schmöller et al., 2015). However, the conditions for ordinary least squares regression are not fulfilled, which may lead to biased results: First, there usually is a large number of zones or stations with zero (or very few) rentals, which needs to be corrected for (by variable transformation or zero-inflated models (Lambert, 1992)). But even more importantly, observations are not independent and error terms are not homoscedastic: Car-sharing (or bike-sharing) demand at a given location may not only depend on the location's characteristics, but also on its neighborhood (spillover effects). In fact, given the limited fleet sizes, all free-floating car-sharing schemes require their customers to walk to the next available vehicle, which may be a couple of hundred meters away.

Dedicated models have been developed to capture auto-correlation in time (Hamilton, 1994) and space (Cliff and Ord, 1973). An overview of the modeling approaches suggested to account for spatial auto-correlation is presented by Griffith and Csillag (1993). In the context of this research, the two most relevant are the *spatial lag* and the *spatial error* model (Anselin, 2009). The lag-model can be used when the spatial auto-correlation only affects the dependent variable, i.e. if dependent variable y_i for zone i is correlated with the dependent variable y_j of neighboring zones $j \neq i$. The spatial error model can account for inter-dependencies due to correlation in unobserved attributes. A combination of the two is the *SARAR* model (Cliff and Ord, 1973):

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

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

with W denoting the spatial weights matrix, λ representing the spatial lag and $e \sim N(0, \sigma_i^2)$. So far, spatial regression techniques have rarely been applied to study demand for shared mobility.

Application in this thesis

In this research, a *SARAR* model (Cliff and Ord, 1973) is used to study the effect of spatial characteristics on free-floating car-sharing demand (Becker et al., 2017b). Predictors include population and workplace density as well as accessibility and mobility tool ownership levels, but were generally limited to the zone characteristics available in the local transport model.

Schmöller et al. (2015) used a simple linear regression model with neighborhood household characteristics (age composition, household size, employees) at a level of detail that was not available in the Swiss analysis. However, other spatial characteristics were not included in the regression analysis and no tests for spatial auto-correlation were conducted.

3.4 SAMPLE BIAS AND TREATMENT EFFECTS

Sample bias may limit applicability of model results to a general population. A classical example is the one of wages and work hours of married women (Heckman, 1974), who are assumed to accept job offers only if conditions exceed a certain (individual) threshold. Uncorrected parameter estimates would consequently indicate a biased (too high) wage rate. Heckman (1979) proposed to address this issue using a two-stage modeling approach. In this approach, a selection equation and the main model equation are estimated jointly with the non-selection hazard (inverse Mills ratio) resulting from the selection model being included in the main model. The approach can be applied both in case of censored observations (restricted sample) and to analyze treatment effects (in case of correlations between selection and outcome).

While the method by Heckman (1979) and its derivatives allow to accurately determine treatment effects for cross-section data, they may not always allow causal inferences. For such applications, panel data models are more powerful tools (Wooldridge, 2002; Cameron and Trivedi, 2004). Such models can be applied to repeated observations of the same sample (balanced panel). Three major approaches have been proposed: In the fixed effects model, changes in the outcome variable are explained by differences in the predictors for each individual i:

$$(y_{it} - \bar{y}_i) = \beta \cdot (x_{it} - \bar{x}_i) + \epsilon_{it}$$

for observation t and ϵ_{it} as homoscedastic residuals. However, parameters can only be identified if the data includes sufficient within-variation (i.e. variations in time for each individual) (Bell et al., 2018).

The random effects model captures variation both *within* an individual i (time evolution) and *between* different individuals. It does so by adding an individual-specific (random) component $\gamma z_i + \nu_i$. The model equation then reads:

$$y_{it} = \alpha + \beta x_{it} + \gamma z_i + (\nu_i + \epsilon_{it}).$$

It is important to note that the random-effects model is efficient and consistent only if none of the predictors is correlated with any unobserved attribute (omitted variable bias). This is in contrast to the fixed-effects model, which provides unbiased parameter estimates in every case (Wooldridge, 2002).

In contrast to the two approaches above, the population averaged (or pooled) model ignores the panel structure of the data. The model then reads:

$$y_{it} = \alpha + \beta x_{it} + \gamma z_i + \epsilon_{it}.$$

In such a models, parameters can be identified even if *within*-variation is small. However, since all observations are (falsely) treated as independent, standard errors are underestimated. Moreover, interpretation is more difficult as there is no clear statistical separation of *within* and *between* effects (Bell et al., 2018).

In the context of shared mobility, the work by Cervero and Tsai (2004) is the only study in the peer-reviewed literature on shared mobility, for which panel data was gathered. The authors used the population-averaged model as well as direct comparisons of the target indicator means (e.g. VKT or car ownership).

Application in this thesis

In this thesis, the two-stage approach by Heckman (1979) has been used to jointly model membership and frequency of use for two car-sharing services (Becker et al., 2017a). This adds a new dimension to earlier research, which either relied on descriptive statistics (Kopp et al., 2015) or on simple models with membership as the only outcome (Juschten et al., 2017). However, also the two-stage model could be extended further. For example, Kopp et al. (2015) introduced a multi-modality index as an interesting further impact of car-sharing membership, whereas Juschten et al. (2017) include more detailed fleet attributes as predictors.

A population-averaged panel data model has been applied in Becker et al. (2018) to estimate the car-ownership impact of free-floating car-sharing. Given the low within-variation of car-ownership and other household characteristics, this was deemed the most appropriate model for the purpose. However, it does not allow to fully elicit the panel structure in the data (compared to a fixed-effects model).

The study is similar to earlier work by Cervero and Tsai (2004). However, there are two main differences: First, the control group consisted of people, who had stated interest in car-sharing, but did not become members. In this thesis, a random sample of the local population was used. Neither of the two control groups can be assumed a perfect match to the respective car-sharing member groups. Yet, given the panel structure in the data, this would only be relevant in case the groups are affected differently by external shocks. The second key difference is that Cervero and Tsai (2004) used a difference-in-differences approach, which only compares the outcome distributions, but does not control for changes in socio-demographic attributes.

Mishra et al. (2015) present an alternative approach to determine the car-ownership impact of car-sharing using cross-sectional data. In their approach, selection bias is controlled for by propensity-score matching. However, the setup still does not allow to address simultaneity bias.

3.5 MATSIM

Implementation of shared mobility schemes requires substantial capital investment as well as support by transportation authorities. Hence, physical test-runs are extremely expensive, so that simulation tools are required to study profitability and externalities of such new services in advance. However, traditional four-step transport models are not designed to capture modes with discrete supply (single vehicles with dynamic availability). In this sense, testing schemes of shared mobility is a perfect application of modern agent-based transport simulation tools.

One of the most widely used of such simulation frameworks is MATSim (Horni et al., 2016). In MATSim, agents of a synthetic population aim to minimize their generalized cost of travel throughout a simulated day.[3] Optimization is done in a co-evolutionary process, in which agents are affected by each others' decisions. Figure 3.1 presents the general setup: An *initial demand* (agents with daily plans specifying the sequence of activities as well as travel modes, routes and departure times) is provided to the mobility simulation *mobsim*. During the *mobsim* step, all agents execute

3 In its standard form, MATSim is designed to model a single day (usually 30 hours from midnight until the early morning of the next day). More recent work aims at extending this period to a whole week (Ordoñez Medina, 2017).

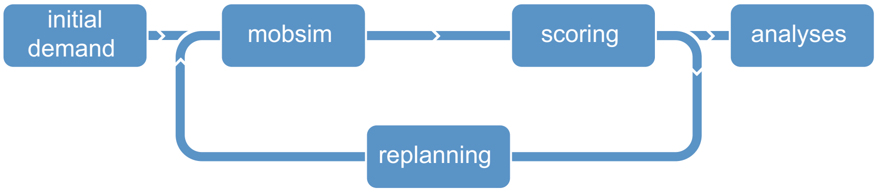


FIGURE 3.1: MATSim loop.
(Source: Horni et al. (2016))

their daily plans simultaneously. The simulation is done second by second. During the simulations agents are affected by each other's actions, so that they may be delayed by congestion or miss their public transport connection. At the end of the simulated day, each agent's performance is assessed using a *scoring* function, which (generally speaking) rewards time spent at activities and penalizes time spent travelling[4] and delays. Some agents are then given the opportunity to alter their daily plan (*replanning*) to improve their score. Choice dimensions usually are travel mode, departure time and route. In addition, research has been conducted to add further choice dimensions such as location of secondary activities as well as adding and dropping activities to/from the schedule (to capture induced demand) (Feil, 2010; Balac et al., 2018).[5] The updated plan is then used in the next iteration. The simulation is usually continued until agent scores reach a stochastic equilibrium. The resulting state is assumed to represent reality. Agents' activities of this final iteration are then used for the main *analyses* of the respective scenario (usually not part of MATSim).

MATSim is particularly well-suited to simulate shared mobility services. It models travel demand and supply at a disaggregate level (individual agents and vehicles) and at very high spatial and temporal resolution (short road segments and seconds). Moreover, agents' decisions immediately affect others (i.e. a shared bike taken by one user becomes unavailable to other users until the rental is completed). A relevant shortcoming of MATSim in this regard is the lack of a short-term re-planning feature: During the *mobsim* step, agents execute their daily plan, but get stuck if e.g.

4 Disutility of travel can be specified per mode and can also include transfers, wait times and access/egress for public transport.
5 The SimMobility tool by Adnan et al. (2015) even includes dynamic land-use patterns, but development is still ongoing and there are less applications of this framework in the literature.

their desired car-sharing vehicle is unavailable.[6] In standard MATSim, the high associated penalty is carried over to the following iterations and may negatively bias usage of shared modes.

Substantial research has already been conducted to simulate car-sharing schemes in MATSim. First implemented by Ciari et al. (2013), the MATSim car-sharing feature has been used for a wide range of studies, such as estimating demand for station-based and free-floating car-sharing (Ciari et al., 2014; Balac et al., 2015), assessing the impact of different pricing schemes on car-sharing use (Ciari et al., 2015a) or studying the impact of parking policies on demand for free-floating car-sharing (Balac et al., 2017). More recent research even allows to cover vehicle rebalancing and competition between operators (Balac et al., 2019). Hence, most aspects of currently available car-sharing schemes can be modeled in MATSim.

In contrast to car-sharing, bike-sharing schemes have rarely been simulated in MATSim. An early implementation was used to study relocation algorithms in station-based bike-sharing schemes (Dubernet and Axhausen, 2014). However, the algorithm is relatively slow and thus unfeasible if combined with other extensions (for car-sharing and bike-sharing). However, the car-sharing extension by Ciari et al. (2016) can be modified to also cover car-sharing.

Ride-hailing has not been subject of specific MATSim analyses yet. However, contributions for taxis and automated vehicles have been developed (Maciejewski, 2016; Hörl, 2017). The existing implementations can model different service areas, dispatching algorithms and rebalancing strategies. Given that in terms of the simulation, the only differences between ride-hailing and automated taxis are the operating cost (and fare)[7], the aforementioned extensions can be easily applied in this context, too.

It has to be noted that MATSim is designed as a transport simulation tool. Hence, it allows to capture system-level impacts of changes in supply and demand. However, as a scenario-based tool, it can only provide insights on a given set of input parameters (e.g. fares, fleet sizes, road capacities), but does not allow mathematical optimization of such attributes. For such research questions, other tools have to be used (compare Brandstätter et al.

6 Usually agents would then switch to public transport to complete their trip, but no alternative available shared modes (or vehicles) will be taken into consideration.

7 Driver scheduling (also for public transport) is not part of MATSim at this point.

(2017) or Deng and Cardin (2018) for applications in shared mobility).[8]

Application in this thesis

In this thesis, MATSim is used for a joint simulation of large-scale car-sharing, bike-sharing and ride-hailing fleets (Becker et al., 2019). Simulating these services as part of the transport system (and in competition with other modes) promises more realistic results. In contrast, Perboli et al. (2018) study different car-sharing fleet sizes and pricing schemes in a Monte-Carlo approach. The simulation is then based on fixed network travel times and fixed demand patterns, neglecting any potential second-order effects of car-sharing use. Yet, these are particularly relevant to determine the scheme's system-level impacts. Anyway, by using a year as analysis horizon, Perboli et al. (2018) point at a worthwhile extension of MATSim to capture longer-term travel behaviour (such as multiple days or even weeks).

8 However, mathematical optimization approaches presented so far only cover very limited areas and rely on an exogenous (static) travel demand.

4

DATA

Not everything that can be counted counts, and not everything that counts can be counted.
— Albert Einstein

Various data sets have been used in this thesis. The two main sources are briefly introduced in this chapter. For a complete list, the reader may refer to the relevant sections of the different papers.

4.1 SWISS MICROCENCUS MOBILITY AND TRANSPORT

The microcensus mobility and transport is a large-scale travel survey carried out every five years. In a computer-aided telephone interview around 60 000 respondents (about 0.7 % of the population) are asked about their socio-demographic background, other household members and their travel behaviour (on one random target day per respondent). In addition, some respondents report their attitudes towards certain transport policy measures, provide in-depth information on long-distance trips or take part in a stated-choice experiment on mode choice. Responses are geo-coded and enriched using spatial information on their home and work location. The survey is commissioned by the Federal Office of Spatial Development (ARE) and the Federal Office of Statistics (BFS).

Raw data sets of the 2005, 2010 and 2015 editions of the survey were available for this research. Providing a representative picture of the travel behaviour of Swiss residents, it was used both as a means of validation, but also as main data source for certain analyses. A limitation with respect to this research is that the microcensus only captures car-sharing membership (and only as a yes/no question), but does not resolve use of different shared modes in more detail. Further information on this data set can be obtained from the Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE) (2017).

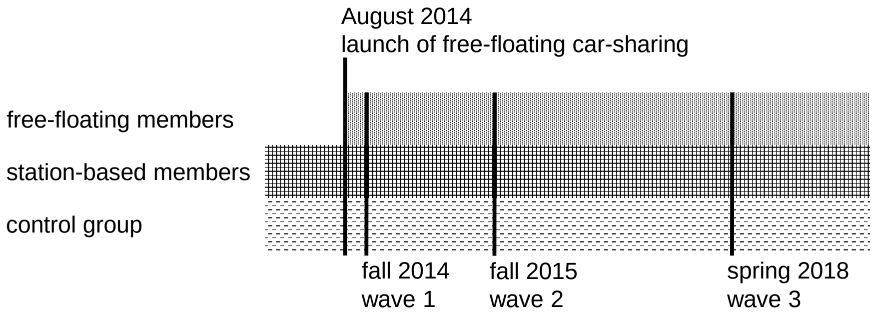


FIGURE 4.1: Study design for mobility study in Basel

4.2 MOBILITY SURVEY IN BASEL, SWITZERLAND

The most important data set used in this research was survey data collected by the author in the course of a research project on evaluating the travel behaviour impact of free-floating car-sharing in Switzerland. As part of this research project a panel survey was conducted with three iterations (compare Figure 4.1). Each iteration (*survey wave*) consisted of a questionnaire capturing the respondents' socio-demographic background[1] as well as a week-long travel diary using smartphone-based GPS tracking. In each survey wave both the respondents of previous waves plus additional respondents were invited (unbalanced panel). Data was collected for three groups: members of the new free-floating car-sharing scheme, members of the long-established station-based car-sharing scheme and a random draw of the local population as control group. Details on the survey design and data collection are provided by Becker and Axhausen (2018).

Partial data from this survey has been used in three papers so far: First, questionnaire data of *wave 2* for all three groups has been used to study user groups and usage patterns (Becker et al., 2017a). Second, questionnaire and travel diary data of free-floating members and the control group of *wave 1* and *wave 2* have been used to measure travel behaviour impacts (Becker et al., 2018). Third, travel diaries of *wave 1* and *wave 2* have been used along with transaction data of the local operator to estimate a first mode choice model with free-floating car-sharing (Becker et al., 2017b).

1 The questionnaire was designed in a way to allow direct comparisons with the Swiss microcensus (see above).

5

SUMMARY OF PUBLICATIONS

As formulated in Section 2.6, the main aim of this research is to study the externalities of shared mobility on the transport system and to show, how positive impacts can be maximized. However, the research question has various facets. Moreover, shared mobility has been a rapidly evolving concept and only station-based car-sharing was a reasonably well-researched shared mode at the beginning of this thesis, whereas little knowledge on the fast-growing free-floating car- and bike-sharing schemes was available. Hence, each part of the thesis covered one aspect of the main research question, using different data sets and analysis methods. The key topics and data sets are:

1. Which role does (station-based) car-sharing membership play in a portfolio of mobility tools? The analysis was conducted based on the Swiss national household travel survey (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012).

2. What are the differences in user groups and usage patterns between station-based and free-floating car-sharing? This question was answered using a member survey (questionnaire plus GPS travel diary) conducted as part of this thesis.

3. How does free-floating car-sharing affect its members' travel behaviour? The same member survey as above was repeated to generate panel-data, which allowed to answer this question.

4. Which are the drivers of demand for free-floating car-sharing? Original transaction data of a free-floating car-sharing operator was available for this analysis.

5. Which fleet sizes and combinations of different shared modes are required to maximize positive externalities? The results from above analyses allowed to generate MATSim simulations to address this question.

The following sections provide a summary of each of the different items.

5.1 MODELING CAR-SHARING MEMBERSHIP AS A MOBILITY TOOL: A MULTIVARIATE PROBIT APPROACH WITH LATENT VARIABLES

The first paper (Becker et al., 2017c) addresses the strategic level of travel behavior (Le Vine, 2011): mobility tool ownership. While earlier research has shown a dualism between car ownership and public transport subscriptions (Simma and Axhausen, 2001), it was largely unclear, how shared mobility is combined with the two traditional options. To address this research gap, a mobility tool ownership model has been developed, which includes car-sharing membership as well as private car ownership and season ticket holdings (regional or national subscription).

Methodologically, the approach goes beyond earlier research in the Swiss context (Simma and Axhausen, 2001; Scott and Axhausen, 2006; Kowald et al., 2017) by using a multi-variate Probit model. This way, it accounts for the fact that choices of mobility tools are not independent, but part of a joint decision on a portfolio of mobility tools. In this framework, season ticket holdings are furthermore modeled in a two-stage approach (Heckman, 1976), because the two types of season tickets are direct substitutes.[1]

As further novelty, also attitudes are included as explanatory variables on car-sharing membership. Although earlier research suggested that car-sharing attracts members of certain milieus (Bongart and Wilke, 2008), attitudes have not been incorporated into models on car-sharing membership before.[2] In this research, two latent variables were identified: *PROFEES* indicating acceptance of further taxation on car traffic and *PROINFRA* indicating endorsement of additional investments into infrastructure for public transportation and active modes.

The model was applied to a pooled dataset of the 2005 and 2010 editions of the Swiss national household travel survey (Swiss Federal Statistical Office (BFS), 2006; Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012). The survey captures socio-demographic information as well as spatial information of home and work locations, attitudes towards transport policies and ownership of mobility tools. Given the countrywide coverage of station-based car-sharing services, information on membership in this scheme has been gathered in

1 The national season ticket includes the local season ticket.
2 An exception is the work by Juschten et al. (2017), which appeared shortly after this paper.

this microcensus since 2005. To allow a direct comparison, also individual univariate Probit (UVP) models were estimated for the different mobility tools.

Generally, the results are in line with earlier research, in that accessibility and spatial structure shape ownership of mobility tools (Loder and Axhausen, 2018). Moreover, higher education, high micro-accessibility of public transport and a high *PROFEES* attitude were identified as drivers of car-sharing membership. While some of these factors have already been identified in the literature (Scott and Axhausen, 2006; Kowald et al., 2017), there are some surprises: For example, macro-accessibility by public transport as well as the distance to the next car-sharing station were not found to have a significant effect on car-sharing membership. A possible interpretation of this is that car-sharing is used only occasionally and for trips beyond the usual (local) activity spheres. Moreover, there is a strong correlation in both observed and unobserved effects between car-sharing and the two season tickets for public transportation, while there is a strong anti-correlation with car-ownership. A likely interpretation is that car-sharing membership is used as a complement to public transportation subscriptions, thus making public transport attractive to a larger group of customers.

The strong cross-correlations also justify the joint modeling approach as presented in this paper. In fact, there are substantial differences in the parameter estimates between the multivariate model and the univariate reference models. Hence, joint modeling of ownership of the different mobility tools is required to avoid biased parameter estimates. Also, the strong effects of the two latent variables indicate that attitudes help to explain ownership of mobility tools.

5.2 Comparing car-sharing schemes in Switzerland: user groups and usage patterns

The second paper (Becker et al., 2017a) studies differences between station-based and free-floating car-sharing. Such insights are key to understand to what extent insights on station-based car-sharing also apply to the newer and fast-growing free-floating car-sharing services. The implementation of the first free-floating car-sharing scheme in Switzerland allowed to address this question.

A survey was conducted to gather socio-demographic information and travel behaviour data[3] of free-floating car-sharing members, station-based car-sharing members and a control group (random sample of the local population). In a first step, a descriptive analysis revealed differences in socio-demographic background as well as usage patterns of the two car-sharing schemes. Based on these results, membership and frequency of use of the two car-sharing schemes are modeled in a two-stage approach (Heckman, 1979). Finally, the (partial) membership model is applied to estimate the market potential of free-floating car-sharing for the five largest cities in Switzerland.

The descriptive analysis reveals that car-sharing members are mostly male and younger than the control group. In both aspects, free-floating members are more extreme than station-based members. Both groups are highly educated, working and describe themselves as particularly open to new products or services. Car-sharing members are exceptionally well equipped with public transport subscriptions, but own substantially fewer private cars instead (although free-floating members own more cars than station-based members).

Despite various similarities in their user groups, the two schemes are used differently: Station-based car-sharing is mostly used for shopping and leisure trips and is booked well in advance. In contrast, free-floating car-sharing serves a broad range of trip purposes (including commute trips), but is selected spontaneously. Moreover, station-based car-sharing appears to substitute private cars (transport of goods, trip would be postponed if unavailable), whereas free-floating car-sharing seems to be mostly used as

3 Respondents were asked to keep a travel diary for one week using a GPS-based tracking app on their smartphone.

faster and more convenient alternative to public transportation.

The differences are also reflected in the subjectively perceived impacts on mode use: Station-based car-sharing generally reduces the use of private car and increases frequency of use for most other modes, free-floating car-sharing does not induce much change in private car use, but it draws trips from other modes.

The descriptive analysis is complemented by a quantitative model to identify drivers of car-sharing membership and use. For car-sharing membership, the model confirms the insights from above, but most interestingly, it shows that frequency of use is determined by different factors. For example, a national season ticket for public transport (GA) is a strong predictor of membership, but has a negative effect on frequency of use.

In a last step, the model was used to predict the market potential of free-floating car-sharing using data from the Swiss national household travel survey (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012). The results suggest a total market size of 7-12 % of the driving population for the five largest cities in Switzerland. However, given that current free-floating membership numbers are not publicly available, the predictions are hard to validate.

Although it does not provide substantial methodological contributions, the paper presents a direct comparison of station-based and free-floating car-sharing schemes operating in the same city. By revealing substantial differences in usage patterns and travel behaviour impacts, it shows that insights gained on one scheme (e.g. reduction in energy consumption) are not necessarily also valid for the other. However, additional research should be conducted to validate these findings for different local contexts.

5.3 MEASURING THE CAR OWNERSHIP IMPACT OF FREE-FLOATING CAR-SHARING – A CASE STUDY IN BASEL, SWITZERLAND

The survey described in Section 5.2 was conducted twice: right after the launch of the free-floating car-sharing scheme and one year later, allowing a before-and-after comparison.[4] The third paper (Becker et al., 2018) made use of this panel structure in the data for an in-depth investigation of its impact on car-ownership and travel behaviour.

Data from both the questionnaires and the GPS-based travel diaries was available for this paper. Responses from free-floating car-sharing members and the control group were used. Station-based car-sharing members were excluded as service characteristics did not change during the study period.

The survey captured the current number of cars per household in each wave (*before* and *after*). In addition, respondents were asked if they anticipated any changes in their vehicle holdings in the upcoming 12 months. Hence, the data allowed to compare the observed level of car-ownership in wave 2 to two reference points: to the observation from wave 1; or to the car-ownership level respondents anticipated for the next year when asked in wave 1. While the first comparison provides an observed effect, the second approach potentially also captures foregone purchases (or sales) of private cars.

A difference-in-differences approach has been used to analyze the impact of free-floating car-sharing on private car-ownership using both reference points. After that, a population-averaged model has been applied, which also captured anticipated changes.[5] The difference-in-differences analysis indicates that 8-13 % of free-floating car-sharing members shed one household vehicle. The range is set by the two possible reference points (see above). The population-averaged model allowed a more precise determination of the reduction rate. In the model, an indicator for *car buying intentions* was interacted with the membership attribute. This approach allows to estimate the car reduction rate separately for members who actually plan to purchase a private car soon (and may just use free-floating car-sharing

4 It is assumed that profound changes in travel behaviour set in only multiple weeks after joining the scheme.

5 A fixed-effects approach would be preferable as it would make full use of the panel structure in the data, but the low variation in individual vehicle ownership did not allow to identify model parameters (compare Section 3.4).

to fill the gap) from members without such prior intentions. Indeed, the model shows that free-floating car-sharing lets its members reduce their car-ownership by 24 %[6], unless they already intended to buy a car upon joining (in which case they would more than double their car-ownership).

The unexpectedly low response rate to the travel diaries did not allow a similar quantitative analysis of the travel diaries (e.g. with respect to car use or energy consumption). Instead, a qualitative analysis of substitution patterns was conducted: For each trip chain in which free-floating car-sharing was used, comparable activity patterns (locations and times) were identified in which free-floating car-sharing was not used. Interestingly, such corresponding patterns could only be found in one in four cases.[7] Hence, free-floating car-sharing is mostly used for non-regular trips. Moreover, in those cases, where a corresponding pattern was found, free-floating car-sharing replaced car trips or inconvenient[8] public transport trips.

The paper is one of the very first in the peer-reviewed literature to determine the impact of free-floating car-sharing on individual travel behaviour. It shows that membership is accompanied by a reduction in private vehicle holdings, at least for some of its customers. Moreover, even on a trip-level, free-floating car-sharing is used as an alternative to the private car or to inconvenient public transport connections. Hence, the service seems worthy of the public support it requires for its operations, such as flexible access to on-street parking.

6 This corresponds to 6 % of members selling (or not buying) one car.
7 Basis were (on average) two weeks of travel diaries - one week per survey wave.
8 e.g. long headway, early mornings / late evenings

5.4 MODELLING FREE-FLOATING CAR-SHARING USE IN SWITZERLAND: A SPATIAL REGRESSION AND CONDITIONAL LOGIT APPROACH

The fourth paper (Becker et al., 2017b) takes a yet other perspective, by using transaction data of an existing free-floating car-sharing operator to study in which areas and in which situations the service is used the most. Although the effect of spatial characteristics on free-floating car-sharing demand has already been analyzed earlier (Schmöller et al., 2015; Kortum et al., 2016), effects of spatial auto-correlation were not considered, potentially biasing the results. Moreover, trade-offs between free-floating car-sharing and other modes have rarely been analyzed before in a quantitative way.[9]

In a first step, a spatial regression analysis was conducted to study the effect of spatial characteristics on the number of rentals starting in an area. Spatial data was available at hectare-resolution from the local transport model (Bau- und Verkehrsdepartement des Kantons Basel-Stadt, 2016). A *SARAR* model (Cliff and Ord, 1973) was chosen to account for spatial auto-correlation in both the number of rentals (spillovers) and unobserved factors. The results indicate that demand for free-floating car-sharing scales with the density of social activities, but not with the number of work places in an area. Demand is particularly high in areas, where a large number of members reside and/or which only have limited access to public transport.

A mode choice model was estimated to understand, in which situations free-floating car-sharing is used. This allows to put choice of free-floating car-sharing into context with alternative modes and the respective service attributes. To include variation in the choice outcome, free-floating car-sharing trip data was pooled with observations from its members' travel diaries (see above). It was assumed that the choice set consisted of free-floating car-sharing, public transport and walk. In addition, a specification including bike as an alternative was tested.[10] For each observed trip, non-chosen alternatives were generated using Google Maps.

9 Both types of analyzes require trip-level transaction data, which is often deemed confidential by car-sharing operators.

10 Private car was not assumed to be a considered option. The strict definition of the choice sets is a major limitation of this research, since it may not reflect the set of alternatives actually considered by the respondent for the given trip. Also, the transaction data did not include information on individual holdings of season tickets for public transport or even car/bike ownership. Hence, assumed cost levels may also not be accurate for each individual. Yet, the available data did not allow to address these limitations.

Although the mode choice model cannot be used for predictions of mode shares,[11] an analysis of the elasticities provides interesting insights. For example, it shows that free-floating car-sharing is more attractive for trips to or from areas, which are not frequently served by public transportation. Moreover, free-floating car-sharing is more likely to be chosen during the night or in case of rainy or cold weather. Furthermore, access walk to the available car-sharing vehicle is valued much less burdensome than access to a public transport stop. Model results are complemented by a descriptive comparison of transaction data and travel diaries: Results indicate that free-floating car-sharing is indeed used, when public transport or walk alternatives take substantially longer time (and/or involve transfers).

Results of this research are useful to better design future service areas of free-floating car-sharing. Moreover, results of the mode choice model can be used to enhance representation of car-sharing in simulation models like MATSim.

11 The alternative-specific constants are biased due to the unrealistically high share of car-sharing trips in the pooled data set.

5.5 ASSESSING THE WELFARE IMPACTS OF SHARED MOBILITY AND MOBILITY AS A SERVICE (MAAS)

While the first four papers provide in-depth insights into existing (free-floating) car-sharing schemes, the fifth paper aims to study the potential impact of different shared modes on a system level. This is done in a scenario-based analysis using the agent-based simulation tool MATSim. It is a novel attempt to simulate multiple schemes of shared mobility jointly.

Scenarios include different fleet sizes for the three modes: free-floating car-sharing, free-floating electric bike-sharing and ride-hailing.[12] In the simulation, the three shared modes compete against each other as well as with the standard modes walk, bike, car and public transport.

However, it is widely expected that shared modes can unfold their full potential only if they become integrated with public transport. The concept of *Mobility as a Service (MaaS)* goes even further by combining all modes including the private car into one offering (either using flat fees or pay-per-use billing) (Jittrapirom et al., 2017). In MATSim, such a MaaS scheme is included by setting the (decision-relevant) variable cost of car travel to cover the full costs of the car trip.[13] This way, it competes with other modes on a level playing field, potentially allowing less biased mode choice decisions.[14]

In addition, integration with public transport is taken to another level, by offering access to shared modes at subsidized fares in lieu of currently unprofitable public transport lines.

Methodologically, MATSim already provides most of the functionality required for the above analyses. They key additions are the derivation of a bike-sharing feature (based on the existing car-sharing framework in MATSim) as well as the implementation of a mode choice model. Since no empirical mode choice model covering all modes was available, partial

12 The three modes were chosen since they were the most dominant services in the large European cities at the time of this research.

13 The underlying idea is to remove the effect of sunk cost due to prior investment into mobility tools. Instead fixed cost components such as acquisition cost or insurance are included in the variable cost.

14 When travellers own certain mobility tools (e.g. cars), a large part of the total travel cost is actually sunk cost (compare chapter 2). Hence, the cost considered for mode choice is artificially reduced, leading to potentially inefficient travel behaviour.

models for the different shared modes had to be combined with the existing MATSim mode choice model (Hörl et al., 2019).

The paper addresses an array of different research questions. Hence, the results provide comprehensive insights into the interactions of the different shared modes, their system-level impacts and their potential to substitute public transportation. In addition, it provides a glimpse at the potential effectiveness of MaaS offerings.

The results indicate that vehicle utilization is highest for fleets of about 1'000 shared cars and bikes and (less than) 250 ride-hailing vehicles. Interestingly, in the scenario of more transparent car costs, utilization-optimal fleet sizes appear only marginally larger. In addition, the analysis suggests that in the current transport system, only ride-hailing services can be operated at a profit. Car-sharing and bike-sharing only become profitable in the case of transparent car costs.

Moreover, the results indicate that spatially, small fleets of free-floating car-sharing and electric bike-sharing compete about trips in the same (central) neighborhoods, whereas ride-hailing covers the whole area almost uniformly. For larger fleets (i.e. availability), patterns of start locations for free-floating car-sharing and bike-sharing approach those of ride-hailing.

On a system-level, car-sharing and ride-hailing reduce total travel times by 2 %,[15] but no substantial impact was found for the generalized cost of travel. Yet, introducing transparent car costs would increase network travel times and generalized cost of travel as this shifts away demand from private cars to slower modes.[16] However, both car-sharing and bike-sharing (but not ride-hailing) are found to substantially reduce transport-related energy consumption, although the impact is much lower as through introducing transparent car costs (25 % less energy consumption).

Finally, it was shown in a small case study that all three shared mobility services are able to provide cost-efficient alternatives to line-based public transportation in lower-density areas. As a side-effect, such substitution

15 Bike-sharing was not found to substantially reduce total travel time.

16 The result is counter-intuitive and may more hint at a methodological limitation: In MATSim, links are simulated as queues following the *first in - first out* principle. However, travel times are not explicitly capacity-dependent (congestion is modeled through spill-back of queues), so that travel time gains in case of a substantial shift away from private cars is underestimated.

would allow an up to 18 % reduction in system-wide energy consumption. However, equity aspects[17] would have to be analyzed to better understand feasibility of such a measure.

Hence, this research shows that shared mobility is a potential method to reduce system-wide energy consumption. Yet, the potential impacts are limited, so that additional services and policies (for example introducing transparent car costs) are required to achieve substantial changes. Moreover, it was shown that (subsidized) shared modes can serve as alternative to public transport operations in lower-density areas.

17 In particular, services would have to be designed such that they are accessible for the whole population, including for example children and elderly.

6 RELEVANCE OF RESULTS

Wait a minute. What did you just say? You're predicting $4-a-gallon gas? ... That's interesting. I hadn't heard that.

— George W. Bush

This research has provided various contributions allowing policy-makers and shared mobility operators to take more informed decisions. In addition, the tools developed in the course of this research may also be useful to address future research questions. In the following, the most relevant contributions are discussed.

6.1 METHODOLOGICAL CONTRIBUTIONS

The first methodological contribution is the mobility tool ownership model presented in Becker et al. (2017c). Although there have been earlier applications of multivariate Probit models in the field of transportation (Yamamoto, 2009; Bhat et al., 2014) and also Probit models with sample selection have been used in other fields (Gulati and Higgins, 2003; Jenkins et al., 2006), the two approaches have not been combined to model ownership of different mobility tools before. Methodologically, the approach therefore fills an important gap between simpler models such as the plain multivariate Probit and more advanced attempts to model mixed types of outcomes (e.g. joint model for car-ownership and residential location) (Paleti et al., 2013; Bhat et al., 2014). The model can be extended to also include other forms of shared mobility.

By studying car-sharing membership in the context of other mobility tools, the model presented by Becker et al. (2017c) also goes beyond other research conducted in parallel, where car-sharing membership was treated in an isolated manner (Juschten et al., 2017). However, the presented model also relies on simplifications. In particular, it assumes a fixed residential location, ignoring potential inter-dependencies with this layer (Pinjari et al., 2008). Yet, it offers a novel approach to account for the underlying joint decision process on a portfolio of mobility tools. A possible application of the model would be in the generation of a synthetic population for Switzerland, where the model can be used to more realistically assign mobility tools to agents.

As a second contribution, this research has provided a new method to simulate bike-sharing schemes in MATSim. Although bike-sharing has been included in MATSim before (Dubernet and Axhausen, 2014), earlier frameworks were computationally too complex, thus substantially slowing down the simulation. As an alternative, the existing car-sharing framework (Ciari et al., 2016) has been adapted to also represent bike-sharing. This required technical innovations on two levels: First, the car-sharing framework had to be modified to allow competing operators of the same service type (i.e. two free-floating operators) as presented by Balac et al. (2019). The second modification concerns the different representations of cars and bicycles in MATSim. While cars are physically routed on the network, bicycles are often *teleported*, i.e. arrival times are calculated based on crow-fly distance, (fixed) detour-factor and fixed speed. To address the obvious shortcomings of such simplifications while still limiting computational complexity, a mixed approach was chosen in this research: bike-share trips are routed on the network to determine the shortest path between origin and destination. Electric bikes are then *teleported* with fixed speed, but using the routed distance.[1] As a result, the new framework allows to simulate free-floating and station-based (one-way and return) bike-sharing. It is furthermore compatible with the latest mode-choice framework for the Zurich scenario (Hörl et al., 2019). Since it is available as open-source software, the framework can also be used for further analyses of bike-sharing schemes, such as optimizing service areas as well as pricing or rebalancing strategies. In addition, the framework can be coupled with earlier work by Ziemke et al. (2017), who present an even more detailed modeling approach for the cycling stage using infrastructure features and socio-demographic attributes.

While the bike-sharing framework already allows for valuable first insights, further extensions appear worthwhile: For example, Hebenstreit and Fellendorf (2018) presented an approach, where bike-sharing can not only be used for one-way trips, but also as access or egress mode for public transportation. Also, they consider charging behaviour of electric bikes, which has been neglected in the current approach. As a result, actual utilization

1 Hence, interactions of bicycles with other modes (especially cars) are neglected. Moreover, elevation profiles are not considered in this research, but can be included without much additional effort (compare work by Dobler and Lämmel (2016)).

of shared bikes would likely be higher than in the simulation, but also operational complexity (thus, costs) will be higher in case of electric bicycles. However, the underestimation of demand is assumed not to be substantial, because Guidon et al. (2019) suggest only limited demand to and from major public transport nodes.

In addition, this research has (re-)introduced existing econometric methods to the car-sharing literature to address various forms of bias in earlier studies. A first example of this is the use of spatial regression techniques in Becker et al. (2017b). Although spatial factors contributing to car-sharing demand have been analyzed before (Stillwater et al., 2009; Kortum and Machemehl, 2012; Schmöller et al., 2015), spatial auto-correlation was neglected. Hence, each zone or car-sharing station was analyzed independently, thus ignoring spillover effects or joint unobserved factors (e.g. proximity to nightlife districts). Using spatial regression techniques, bias in parameter estimates can be reduced. A similar approach as in Becker et al. (2017b) has later also been used to study demand for an electric bike-sharing scheme in Zurich (Guidon et al., 2019).

Another contribution is the panel-data approach to study free-floating car-sharing impacts (Becker et al., 2018). Although already used in an early study on travel behaviour impacts of station-based car-sharing (Cervero and Tsai, 2004; Cervero et al., 2007), later studies were based on respondents' retrospective self-reporting. While this is clearly the least expensive and least burdensome option, validity of the results is endangered by potential response bias, attribution bias and confirmation bias, among others. As a result, reported impacts range from 7-23 private cars replaced per station-based car-sharing vehicle. Making use of the panel structure in the data can lead to substantially higher confidence in the results.

6.2 FINDINGS

The most important contributions of this thesis are the findings with respect to the usage patterns and potential system-level impact of shared mobility. As already noted above, a major focus of this work was on station-based and free-floating car-sharing. However, some of the learnings can also be applied to other shared modes. In the following, the key findings are discussed.

Insights from the mobility tool ownership model (Becker et al., 2017c) confirm that there is a clear divide between private car owners and holders of public transport subscriptions. Moreover, station-based car-sharing membership was found to be driven by the same factors as public transport subscriptions.[2] An immediate interpretation is that station-based car-sharing is mostly used to complement an otherwise public transport-based lifestyle. Thus, members use car-sharing in the rare cases in which they cannot conveniently get to their destination with public transport (or have larger items to carry (Becker et al., 2017a)). However, shared mobility could serve not only as a complement to public transport, but also as a substitute in certain situations: Especially at locations or times with low demand, operating fixed bus lines at acceptable frequencies is expensive and inefficient. Simulation results in Becker et al. (2019) suggest that it would be more economical to subsidize use of shared modes instead. Such an arrangement would acknowledge that shared mobility actually is another form of public transport.[3]

The comparative study (Becker et al., 2017a) indicates that there are certain differences in the user groups between free-floating and station-based car-sharing. Free-floating members are generally young, predominantly male and earn above-average salaries. In these characteristics, they are even more extreme than customers of station-based car-sharing. In addition both groups are particularly well equipped with public transport subscriptions (especially with the nation-wide season ticket (GA)). Yet, free-floating car-sharing members own more cars than station-based members (although still substantially less than the control group). Even more pronounced differences can be observed in the usage patterns, for example regarding trip purpose, planning horizon and substituted mode: While free-floating car-sharing appears to be mostly used spontaneously as a faster and more flexible alternative to public transport, station-based car-sharing is generally reserved in advance and used as substitute for a (private) car. Such differences in user groups and usage patterns have two major implications: First, the differences appear large enough so that the two services do not cannibalize each other. Second, insights from earlier research on station-based car-sharing (demand patterns, travel behaviour im-

2 Still, in a few cases station-based car-sharing is used as additional household vehicle.
3 There are obvious equity and accessibility issues which would have to be addressed before implementing such a framework. However, this is beyond the scope of this research.

pact) are likely not transferable to free-floating car-sharing. In fact, results in Becker et al. (2018) suggest that the impact on private car ownership of free-floating car-sharing is much lower (although still significant). Also, free-floating car-sharing shows much less of a leverage effect on private car use: while station-based car-sharing was found to generally decrease private car travel, it increased use of all other modes. In contrast, free-floating car-sharing appears to draw demand from across the board (Becker et al., 2017a).

Furthermore, Becker et al. (2018) showed that car-sharing impacts vary by customer group. More specifically, the results indicate that some members use car-sharing as an interim solution until they acquire a private car, while other members (who did own cars before) may drop their private cars due to the service. Also parallel research found that car-sharing impacts may vary by customer segment (Giesel and Nobis, 2016; Le Vine and Polak, forthcoming). In the future, much can be learned from an even more differentiated analysis.

Despite its lower impact on car-ownership, it was shown that there is substantial demand for free-floating car-sharing in the larger Swiss cities (Becker et al., 2017a). With 6-12 % of the driving population, this would even exceed the current customer base of station-based car-sharing (2.5 % of all license holders across the country (Becker et al., 2017c)). However, also given that (free-floating) car-sharing is generally used for non-regular trips (Becker et al., 2018), it is unlikely that it will reach a substantial mode share anytime soon. Also, in Becker et al. (2019) it is shown that a fleet of one or two thousand vehicles would be enough to efficiently serve demand in Zurich.[4]

Results from Becker et al. (2017a) indicate that free-floating car-sharing is used in lieu of public transportation.[5] However, the mode choice analysis in Becker et al. (2017b) suggests that free-floating car-sharing trips usually start or end in areas with limited public transport micro-accessibility[6] and that comparable public transport connections would take substantially

4 This is far less than expected by Ciari and Becker (2017) for a case in which free-floating car-sharing would replace the whole car demand in the greater Zurich area.

5 Respondents were asked, what they had done if free-floating car-sharing had not been available for their last trip. The most-chosen reaction was to use public transport instead (Becker et al., 2017a).

6 This is also supported by the spatial regression analysis in Becker et al. (2017b).

longer. Hence, the service bridges gaps in the public transport network rather than being a mere competitor. This is also in line with findings from the travel diaries (Becker et al., 2018) indicating that free-floating car-sharing usually substitutes an inconvenient public transport connection or is used to replace a car-tour with a free-floating car-sharing trip plus (for example) a public transport trip.

While the above results suggest that there are positive externalities induced by free-floating car-sharing,[7] empirical results could only be obtained from small-scale services. Moreover, the overall impact on transport-related energy consumption was still unclear. Research in Becker et al. (2019) complement these findings by simulation of large-scale fleets of free-floating car-sharing, but also electric bike-sharing and ride-hailing. Results indicate that in the current setting, only ride-hailing could be operated at a profit, but would also increase transport-related energy consumption. In turn, car-sharing and bike-sharing reduce energy consumption, but operate at a loss.[8] Yet, none of the modes can produce substantial impacts on system-level generalized cost and energy consumption. However, simulation results also show that shared modes could be part of a comprehensive MaaS offering, which (when also introducing more transparent cost of private car travel) may have a considerable impact on energy consumption.

The results of this research are relevant for both transportation authorities and (potential) operators of shared mobility. The former can learn what to expect of the different forms of shared mobility, which services are worthy of public support and how to best integrate (or regulate) these new modes in the existing transport system. In turn, operators of shared modes can better target potential customers, optimize their service areas, and validate their business models. Actually, most of the mid-term developments in the transport system will likely be shaped by an interplay of public and private actors, which can both use results of this research to inform their strategy.

7 There is less space consumption due to reductions in private vehicle holdings (Becker et al., 2018) as well as a more efficient alternative for inconvenient public transport connections (Becker et al., 2017b).

8 Given that none of the free-floating or ride-hailing operators in Switzerland publish the respective profit and loss statements, this simulation result is hard to validate. However, ride-hailing appears to be well established, while many bike-sharing operators have either withdrawn from the city or rely on public support. Free-floating car-sharing has not been available in Zurich yet.

7

CONCLUSION AND OUTLOOK

They always say time changes things, but you actually have to change them yourself.
— Andy Warhol

Three *revolutions* are commonly expected to disrupt the transport system: vehicle automation, sharing economy and electric propulsion. At the same time, continuing urbanization and tightened sustainability goals call for a more efficient transport system, i.e. one which minimizes travel times as well as space and energy consumption. This research analyzed the impacts that can be expected from shared mobility, isolated from other, parallel developments.

The results indicate that the travel behaviour impact of shared mobility on the transport system depends on the actual form of the service. But even in the best case, potential improvements in system efficiency or reductions in energy consumption are only marginal. Instead, policy tools such as *Mobility as a Service* approaches (which make use of shared modes) are more promising drivers of change.[1]

In a way, such an even further integration is the logical next step after the introduction of shared mobility. By bridging gaps in the public transport network, shared modes often make a public transport-based lifestyle more attractive. However, there still is a dualism between public transport (which also includes shared modes) and private cars. *Mobility as a Service* would allow to overcome this market segmentation and can lead to a more optimal (and more energy-efficient) travel behaviour. As shown in this research, the resulting positive externalities would be substantial.

Achieving such a resource-efficient integrated transport system will require considerable regulation (e.g. fleet sizes, fares, service levels). Hence, a public actor would have to take control over transport supply across all modes and grant concessions to mobility operators and levy sizeable taxes

1 In many cases, shared modes will play a key role as a means to extend the reach of public transport networks.

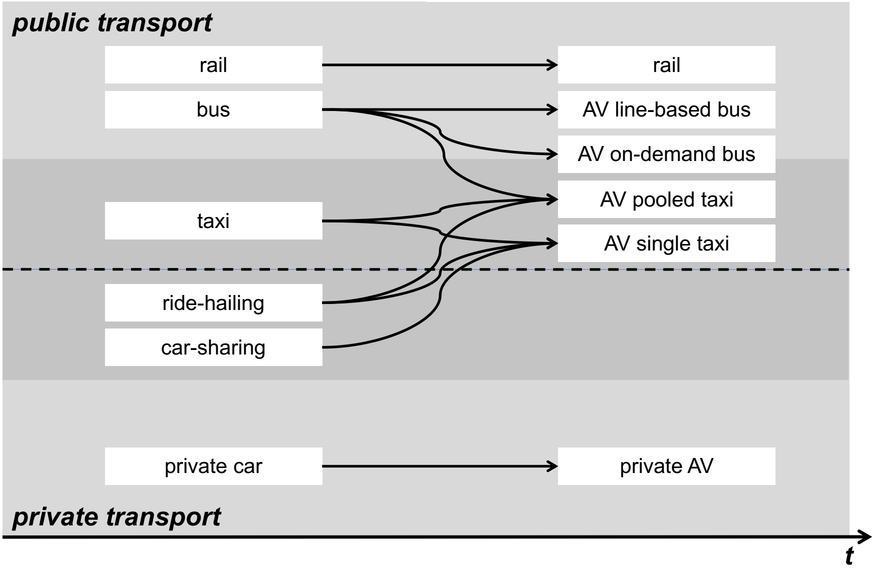


FIGURE 7.1: Potential convergence of travel modes through automation

and congestion charges on private car users. Apart from unclear public support for increased charges for car users, this would be a complete reversal of the current start-up culture which has contributed much of the recent innovations. Yet, such a development would resemble the development of public transport almost 100 years ago: First developed by innovators and investors, operations were soon taken over by public authorities, which then integrated the different services.

An alternative path of future developments would involve less regulation. But also in this scenario, it can be expected that providers of individual (shared) mobility operators will combine their services to make them more attractive to users.[2] However, it is still unclear, which policy measures would allow to effectively manage such a transport system with many different public and private actors.

The convergence of public and private modes into integrated services will be further accelerated by the development of automated driving technolo-

2 An example of such mergers is the recent announcement of a joint venture by Daimler and BMW (http://fortune.com/2019/02/22/daimler-bmw-urban-mobility/)

gies. Such innovations would allow shared vehicles to relocate autonomously anticipating future demand patterns or moving towards an assigned customer. This might not only substantially increase attractiveness of shared modes, but could also allow a higher utilization of the shared fleets. Moreover, vehicle automation may spark invention of new (shared) mobility services, which will then further reduce travellers' need to own a private car (compare Figure 7.1). However, the economics of the new modes as well as their impact on the transport system will need to be studied in more detail.

While the energy consumption impacts of vehicle automation are still unclear, electric propulsion may actually help to further increase positive externalities of shared modes. In fact, the benefit could be two-fold: An immediate benefit would be a decrease in consumption of fossil fuel. In addition, larger fleets of shared modes can also provide a base-load for a city-wide network of charging stations. The higher availability of such charging stations may in turn motivate even private vehicle holders to change towards an electric car.

On a final note, research on the impacts of the *three revolutions* in transportation has focused on the larger cities and their suburbs so far. However, most municipalities in Switzerland are either rural or smaller cities. Given their substantially different transport networks and demand patterns, determining the impacts and possible applications of shared modes (and automated/electric driving) requires further research efforts.

The *three revolutions* in transportation will likely bring about a large diversity of new business models and mobility services. In this research, it was shown that the positive externalities of shared mobility are limited and may only be elicited using heavy regulation. Also a combination of vehicle automation and electric propulsion may not substantially change this picture. Hence, transport planners will need to assume an active role in managing such new services to seize their benefits for the transport system.

A

MODELING CAR-SHARING MEMBERSHIP AS A MOBILITY TOOL: A MULTIVARIATE PROBIT APPROACH WITH LATENT VARIABLES

This paper has been published as: Becker, H., A. Loder, B. Schmid and K. W. Axhausen (2017c) Modeling car-sharing membership as a mobility tool: A multivariate Probit approach with latent variables, *Travel Behaviour and Society*, **8**, 26–36

ABSTRACT

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

CONTRIBUTIONS

H. Becker and A. Loder developed the study design. A. Loder provided the code for the multi-variate Probit model and adapted it for this research. B. Schmid contributed the analysis and code for the latent variables. H. Becker prepared the literature review, pre-processed the data and conducted the model estimation. All authors were involved in interpretation of the model results. H. Becker furthermore took the lead of the project and prepared the manuscript. K.W. Axhausen supervised this research throughout all stages.

A.1 INTRODUCTION

Arranging one's individual transportation requires various choices at different levels, of which many are interdependent. In particular, the strategic decision to own a certain mobility tool, e.g. a car, largely determines the later tactical decisions on mode choice and therefore shapes individual travel behavior (Le Vine et al., 2011). Yet, interdependencies do not only occur between the different levels of transportation choices, but also within them. For example, it has been shown that car owners are less prone to subscribe to a season ticket (Simma and Axhausen, 2001), whereas season-ticket holders in turn may be more likely to become car-sharing members (Becker et al., 2017a). In this analysis, it is assumed that the choices on mobility tools are made simultaneously. As such multiple choices may share common underlying unobserved factors and one outcome might be an endogenous factor in another outcome, jointly modeling multiple outcomes accounts for interdependencies and provides deeper insights into the decision making process (Bhat, 2005; Bhat and Sen, 2006; Bhat et al., 2014, 2016).

For a long time, (motor-)bikes, private vehicles and public transportation subscriptions were the only relevant mobility tools. However, in the recent years, car-sharing was established as additional option providing their members with short-term access to vehicles on an as-needed basis. The schemes attract both scientific interest and customers around the world (Shaheen and Cohen, 2013).

The literature suggests that station-based car-sharing reduces private vehicle ownership as well as vehicle kilometers travelled (Muheim and Reinhardt, 1999; Lane, 2005; Martin and Shaheen, 2011a), although there has been less agreement on the magnitude of this impact (Chen and Kockelman, 2016). Moreover, previous research has consistently revealed that car-sharing schemes blossom best in dense urban areas with a good public transportation supply and mainly attract young, highly-educated, higher-income, urban, car-free and single-household residents (Millard-Ball et al., 2005; Sioui et al., 2013; Becker et al., 2017a).

One major limitation of previous research is that it has not sufficiently accounted for the apparent causal interrelation and jointness of car-sharing membership with the ownership of other mobility tools (Mishra et al., 2015). Instead, the level of car-ownership or the availability of season tickets usually were used as possibly endogenous explanatory variables when modeling car-sharing membership. This however disregards that all three are (simultaneous) outcomes of the same underlying decision process on a portfolio of mobility tools.

Another limitation is that most previous research on factors influencing car-sharing membership has mainly focused on socio-demographic factors ignoring the role individual attitudes and lifestyles play in such decisions (Bongart and Wilke, 2008; Ciari and Axhausen, 2012).

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

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

A.2 BACKGROUND

A.2.1 *Mobility tools in Switzerland*

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

In Switzerland, the most common mobility tool is the private car. It represents an average yearly investment of CHF 6 600 (average annual gross income per household: 121 000 CHF[1]; 1.00 CHF = 0.70 USD[2]) and subsequently allows inexpensive and flexible mobility at an average of CHF 0.27/km[3]. However, given the particularly well-developed network, public transportation in many cases is a competitive alternative to cars and in some (i.e. travel between the larger cities), it is even superior. While a GA travelcard allows for unlimited travel within the entire public transport network throughout the country, a local season ticket provides access to public transportation within a defined zone or corridor. A GA travelcard has a cost similar to a car: It requires a substantial fixed investment of CHF 3 655 (2nd class) or CHF 5 970 (1st class) per year[4] for the first family member followed by almost no marginal costs. Discounts for additional family members apply. The least expensive option are local season tickets starting at around CHF 700 per year.

The fourth option is a membership of the national car-sharing operator, which provides access to vehicles at almost 1 500 car-sharing stations throughout the country. Dating back to 1987, this station-based car-sharing scheme presents an interesting case, because it is available not only in larger cities, but also in smaller towns and villages. Therefore, it is probably the only scheme worldwide offering a seamless system covering an entire country. It offers its 127 000 members access to almost 3 000 vehicles of various types at 1 500 car-sharing stations (often located at train stations or other central areas)[5]. Members can either: buy a share of the cooperative (one-time investment of 1 250 CHF of which 1 000 CHF is refundable upon exit), or subscribe to the service for an annual fee of 200 to 300 CHF. The mem-

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

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

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

4 prices as of 2015

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

bership fee can be substantially reduced to CHF 25 for holders of a public transportation subscription, although these members pay higher rental fees. Rentals are charged both by the hour and by distance travelled (currently 3 to 4 CHF/h plus 0.50 to 1.00 CHF/km, depending on the vehicle type and time of the day).

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

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

TABLE A.1: Swiss distribution of mobility tool ownership based on micro census mobility and transportation ($N = 8\,477$ - including respondents over 18 years of age and including respondents without drivers license) (Swiss Federal Statistical Office (BFS), 2006; Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012).

A.2.2 *Car-Sharing*

In addition to the station-based car-sharing scheme presented above, new peer-to-peer and flexible one-way car-sharing schemes (Shaheen et al., 2015) have been launched in the recent years. However, earlier research shows that the actual user groups and usage patterns of such more flexible schemes are substantially different from station-based round-trip car-sharing (Becker et al., 2017a). In Switzerland, the first scheme of this kind only started to operate in summer 2015. Therefore, this analysis is restricted to the traditional form, station-based round-trip car-sharing.

So far, most of the literature dealing with station-based (round-trip) car-sharing discusses the market segmentation, environmental impacts or operational issues. In the stream of market segmentation, two sorts of methodological approaches have mainly been used to determine the socio-demographic characteristics of station-based car-sharing members: Most studies have used member surveys to gather socio-demographic information about car-sharing adopters and compared the results with either a control group or a population census. In addition, members were usually also asked for their motivations to become car-sharing members, although those motivations were not cross-referenced to their respective socio-demographic background. Such surveys have been conducted in various (mostly industrialized) countries around the globe and consistently found that car-sharing is particularly attractive to 25-45 year olds of higher educational levels and higher incomes living in smaller households (Millard-Ball et al., 2005; Cervero et al., 2007; Martin and Shaheen, 2011b; Becker et al., 2017a). Only a small fraction of such surveys included attitudinal questions, although there is evidence that car-sharing is particularly successful in certain social milieus (Burkhardt and Millard-Ball, 2006; Bongart and Wilke, 2008; Ciari and Axhausen, 2012). As a second approach, geographic information system (GIS)-based analyses have been used to identify neighborhood characteristics, which support car-sharing membership or usage. Such studies confirmed the role of several socio-demographic characteristics and revealed the importance of public transportation access, parking pressure and population density for car-sharing adoption (Celsor and Millard-Ball, 2007; Stillwater et al., 2009).

Both methodological approaches have addressed the role of private vehicle ownership finding that car-sharing members are more likely to live in car-free households than their peers (Sioui et al., 2013) and that car-sharing attracts households with fewer cars (Martin and Shaheen, 2011a). Moreover, earlier results indicate that car-sharing membership encourages the use of public transportation and active modes at the expense of car use (Martin and Shaheen, 2011a; Mishra et al., 2015; Becker et al., 2017a).

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

Therefore, the actual role of car-sharing in a portfolio of mobility tools is still largely unclear. This research aims at filling this gap by studying the causal background of car-sharing adoption using the Swiss micro census, the national travel survey (Swiss Federal Statistical Office (BFS), 2006; Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012). In doing so, it also accounts for the effect of individual attitudes on mobility tool ownership decisions.

A.2.3 *Modelling mobility tool ownership*

A number of static and dynamic modelling approaches exist to model ownership of mobility tools at the individual and household level. The work by de Jong et al. (2004), de Jong and Kitamura (2009) and Anowar et al. (2014) provides a comprehensive overview and evaluation of various approaches. It is important to note that most of the approaches in the literature merely address the question of car-ownership. So far, only a small number of papers also includes other mobility tools such as motorbikes (Yamamoto, 2009) or subscriptions for public transportation (Simma and Axhausen, 2001; Scott and Axhausen, 2006; Kowald et al., 2017). Moreover, there has only been one attempt to capture the different valuations of fixed and variable costs in car ownership decisions (Tanner and Bolduc, 2014). In the literature, there are two ways of modelling car-ownership: either as indicator for car availability or as number of vehicles in a household. There is broad consensus that the second approach preserves most information (Anowar et al., 2014).

Although widely used in early models on car-ownership, basic multinomial or ordered Logit approaches (Potoglou and Susilo, 2008) may yield unrealistic results when applied to model the choice between multiple mobility tools given that the choices are not mutually exclusive. One way to circumvene this problem is to estimate separate binomial Logit models for each mobility tool (Kowald et al., 2017) or every possible combination of mobility tools. However, such an approach cannot capture unobserved correlations between the alternatives and does not account for the fact that some mobility tools may be used in clusters.

In contrast, in the multivariate Probit approach, multiple correlated binary choice outcomes are modeled simultaneously, allowing to account for correlations in the error terms between the individual choice outcomes (Greene, 2012) rather than explicitly modeling each combination of choice outcomes as in the multinomial case. Recent work by Bhat et al. extended the multivariate Probit to accommodate mixed types of outcomes, e.g. multinomial or ordered outcomes, in which common unobserved factors and endogeneity might be present (Bhat et al., 2014). The multivariate Probit also allows to accommodate truncated samples (Gulati and Higgins, 2003; Jenkins et al., 2006) as well as spatial and social interaction (Bhat et al., 2016).

Various studies have made use of the multivariate Probit approach in transportation. For example, Yamamoto (2009) applied the trivariate Probit model to describe car, motorcycle and bicycle ownership in Osaka and Kuala Lumpur, whereas Mokhtarian and Tang (2013) use it to study choices of shopping channels for clothing purchases. In addition, the bivariate ordered Probit model was used for model the number of different mobility tools at the household level, e.g. car and motorcycle ownership (Sanko et al., 2012; Andrés and Gélvez, 2014) or car and season ticket ownership (Scott and Axhausen, 2006). Dias et al. (2017) also used a bivariate ordered Probit model to study the frequency of use of car-sharing and ride-sourcing services. All studies mentioned above found significant correlations across choice outcomes meaning that common unobserved factors are at work. The research presented in this paper builds upon this earlier research and uses a multivariate Probit approach to jointly model the ownership of different kinds of mobility tools.

A.3 DATA

A.3.1 *Swiss transportation micro census*

This research is based on data from the Swiss national travel surveys (micro census) of 2005 and 2010 (Swiss Federal Statistical Office (BFS), 2006; Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012). The micro census is a quint-annual national CATI survey covering a substantial share of the Swiss population. It provides detailed information on household demographics as well as socio-economic information and travel patterns on the individual level for at least one household member. A share of the respondents was further asked policy questions allowing to infer individual transport policy attitudes. Table A.2 presents the size of the available datasets. The micro census covers persons older than 6 years. However, for this analysis, only respondents above legal and car driving age (18 years) are considered.

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

Car-ownership information is captured by two questions: On the household level, there is a question asking for the number of cars registered in the household (numeric), and on the individual level, there is a question asking whether the respondent had access to a car (levels: always, upon consultation, never). Given its more direct effect on travel decisions, the latter variable was used in this analysis. This is in contrast to the recommendation by Anowar et al. (2014) to use the number of cars at household level, because the micro census captures disaggregate information on individual mobility tool availability for only one household member. A car was assumed an available mobility tool if it was *always* available, the option *upon consultation* was counted as unavailable.

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

TABLE A.2: Number of observations in the micro census.

A.3.2 *Data enrichment*

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

In a first step, some of those variables included in the 2010 data, but missing in the 2005 data were added to the 2005 data. This concerns mainly the level of service (micro-accessibility) of public transportation[6] at the individual home location as well as the spatial structure at the given work place. In a second step, variables missing in both data sets were added. In particular, municipal accessibility scores (for both car and public transportation) of the individual home locations were obtained from Axhausen et al. (2015a). The accessibility scores were then decomposed into three principal components describing *general accessibility*, *comparative higher accessibility of public transportation* and the *comparative higher accessibility to work places* (Loder and Axhausen, 2018). In addition, the distance to the closest car-sharing station was calculated using the individual household coordinates and the station locations of the national car-sharing provider Mobility (Mobility Car-Sharing, 2017).

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

6 The level of service was assigned based on the individual household coordinates from the micro census and a shape file with the level of service zones provided by Bundesamt für Raumentwicklung (2017). The classification of the spatial structure was conducted based on the (available) workplace municipality code. The information was then passed through from the available information on municipality code and spatial structure from the home locations in the micro census.

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

A.4 ATTITUDES

A.4.1 *Data and factor structure*

The micro census data used for this research (Swiss Federal Statistical Office (BFS), 2006; Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012) also contain self-reported attitudes towards transport policies, e.g. different forms of mobility pricing and infrastructure investments. Responses to attitudinal questions are coded in an asymmetric 3-point Likert-scale (1 = disagree; 2 = potentially agree; 3 = agree). For this research, latent constructs are calculated based on those questions included in both the 2005 and the 2010 data set.

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

An exploratory factor analysis was conducted to reduce the data to the most essential elements and to determine the latent constructs (number of latent variables) for the subsequent analysis. Based on the factor-Eigenvalue plot, the results of a parallel analysis and the latent-root-criterion (Hayton et al., 2004), two latent variables consisting of highly related items were retained, explaining the most important dimensions of variability. The factor loadings as reported in Table A.3 can be interpreted as correlations between the factor and corresponding items. A higher factor loading (in absolute value) means that the respective item is more representative of the factor. As shown in Table A.3, the resulting factor structure is meaningful and statistically robust (acceptable goodness-of-fit measures for factor reliability and correlation structure). The two retained factors may be described as follows:

- **PROFEES**: The PROFEES factor (F1) exhibits high positive loadings on items demanding the introduction or increase of road traffic fees (tunnel, peak hour, parking and fuel) and not spending the revenues of such fees on the road infrastructure,

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

Estimation method: Maximum likelihood
Rotation method: Orthogonal varimax
Variance explained: 62.0%. Cronbach's Alpha: 0.63
Kaiser-Meyer-Olkin measure of sampling adequacy: 0.75
Likelihood-ratio test: 2 factors vs. saturated: $p < 0.001$
Number of subjects for factor analysis: 6 952

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

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

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

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

TABLE A.4: Socio-economic characteristics used.

A.4.2 *MIMIC model to predict latent variables*

This subsection presents the methods used to calculate the latent variables, i.e. the attitudes towards pricing schemes and infrastructure investments, which are later used as explanatory variables to better describe the choice of different mobility tools. Although this sequential estimation approach is neither efficient nor consistent (Bolduc and Alvarez-Daziano, 2010; Raveau et al., 2010), its has often shown identical qualitative implications as in a simultaneous estimation approach (Schmid et al., 2016).

The modeling strategy followed in this research is to first predict the two latent variables ("first-step" predictions) for the full sample, a method that relies on the rather strong assumptions of joint normality and values missing at random (or the weaker assumption of covariate-dependent missingness; (Li, 2013)).[8] These "first-step" predictions are then used to impute the missing values by estimating Ordered Logit (OL) models with the attitudinal items as dependent variables. The OL approach has the main advantage that it accounts for discrete nature of the items (3-point Likert-scales) which also are asymmetric (i.e. given the second category "potentially agree"), for which a linear measurement model would be inadequate (Daly et al., 2012). Given that the "first-step" predictions have a high explanatory power (they are, of course, highly correlated with the corresponding items) and that only very few items of a specific respondent are missing, the imputation strategy can be assumed to be reasonably accurate.

Based on the factor structure and corresponding items from above, for both latent variables in Table A.4, a multiple-indicator-multiple-cause (MIMIC) (Jöreskog and Goldberger, 1975) structural equation model (SEM) (Bollen, 1989; Golob, 2003) was estimated. This was done by simultaneously modeling an OL measurement equation linking the latent variables with the items assumed to affect the latent constructs and a linear structural equation for the exogenous variables affecting the latent variables. Once the coefficients are estimated, they can be applied to predict the distribution of attitudes for a population of interest.

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

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

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

8 The test for joint normality of items (H_0) was rejected. However, the test for covariate-dependent missingness (H_0) of items was accepted. The modeling approach is similar to the one shown in Equations 1-4, but assumes linear instead of Ordered Logit measurement equations, which is necessary to apply the maximum likelihood with missing values approach (Stata Press, 2013). This procedure helps to overcome the case-wise deletion of rows containing missing values.

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

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

$$LV_{i,n} = Z_{i,n}\kappa_i + \omega_{LV_{i,n}} \tag{A.4}$$

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

Table A.5 presents the results of the MIMIC model. The results of the measurement model as given in the top rows confirm the findings of the factor analysis shown in Table A.3: For *PROFEES*, increasing fuel and parking prices (FP, PF) exhibit the strongest effect on the latent variable, whereas road revenues for road infrastructure improvements (RR) show the weakest (and negative) effect. For *PROINFRA*, spending road revenues on environmental protection (REN) exhibits the strongest effect. The effects of socio-economic characteristics on the latent variables are presented in the bottom rows. The model shows that increasing *PROFEES* attitudes are mainly affected by lower household size, increasing age, higher income and education, the number of bikes, season ticket ownership and living in the German-speaking part of the country. Increasing *PROINFRA* attitudes are mainly affected by being male, a lower household income, higher education, the number of bikes, season travelcard ownership and an urban home location. Finally, the correlation between *PROFEES* and *PROINFRA* of about 0.17 ($p < 0.001$) is moderate and plausible: infrastructure and environmental protection expenses have to be funded somehow and fees on car use may be regarded as a possible way to generate the necessary funds.

A.5 MODEL FORMULATION

For the main analysis, only holders of a drivers license are considered. The distribution of mobility tools for this subsample is presented in Table A.10. Although dropping observations without drivers license may bias the general distribution of mobility tool ownership, we argue that car-sharing as a mobility tool is unavailable to non-license holders. Therefore, modeling car-sharing as mobility tool for non-license holders would be wrong. It has

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

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Cutvalues κ_{att_i} not reported.

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

to be noted that dropping responses without drivers license changes the socio-demographic composition of the sample given that the possession of a drivers license has substantial positive correlation with the household income as well as the level of education and substantial negative correlation with age. An alternative way to deal with this issue would be to regard car-ownership and car-sharing membership of non-license holders as censored observations and treat them in a sample selection approach (Heckman, 1976). However, this approach was not pursued given that the correlation of the error terms ρ between the main regression (on car availability) and selection equation (on drivers license holding) is not significantly different from zero.

Of the four mobility tools, the two season tickets are direct substitutes.

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

In this setup, the second-level outcome is only observed for those respondents holding a season ticket. Therefore, the model takes the form of a multivariate Probit model with sample selection, a Probit extension of the Heckman (1976) model for truncated samples. Both the multivariate Probit, e.g. (Bhat et al., 2014; Yamamoto, 2009; Scott and Axhausen, 2006), and the probit with sample selection, e.g. (Gulati and Higgins, 2003; Jenkins et al., 2006; Van der Straeten et al., 2003), are well-established methodologies. Also the bivariate probit with endogenous treatment is widely used in some disciplines (Deadman and MacDonald, 2004; Morris, 2007; Bryson et al., 2004; Carrasco, 2001) and has recently been extended by Bhat and his colleagues to model mixed types of outcomes (Paleti et al., 2013; Bhat et al., 2014).

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

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

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

Table A.6: Model equations

their combination. The 12 possible outcome combinations are given in

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

The vectors β_1 to β_4 and the entries of the correlation matrix Σ_4 are the coefficients to be estimated. All parameters are estimated by maximum simulated likelihood (Cappellari and Jenkins, 2006). The associated log-likelihood function is defined as the sum over all N individuals' chosen outcome combination probabilities P:

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

where δ_{ij} is an indicator variable for observation i and outcome combination j. The entries of the correlation matrix Σ_4 are not estimated directly. Instead, the Cholesky factors resulting from the associated Cholesky decomposition of Σ_4 are used. The requirements for model identification follow common procedure, but the interested reader is directed to the work by Bhat et al. (2014) and Cappellari and Jenkins (2006) for a more detailed discussion. Maximum simulated likelihood estimators are consistent, asymptotically normal, and efficient if the number of draws approaches infinity faster than the square root of the number of observations (Train, 2003). For model estimation in Stata[9], the built-in option of robust standard errors was chosen.

A.6 RESULTS

Following the methodology outlined above, the ownership of the four mobility tools was modeled jointly. In order to obtain the best model fit, various combinations of covariates were tested iteratively using subsamples of the data. The final model was estimated based on the complete data set (micro census 2005 and 2010, adult respondents with the attititudes-module

9 The code is available upon request.

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

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

only) using 250 random draws. Table A.8 presents the results both for the multivariate Probit model and for individual univariate Probit models for comparison. However, given that Table A.9 indicates significant correlations, only the results of the joint model are used for interpretation.

As shown in the table, there are significant differences between the results of the two modeling approaches, in particular in the effects of accessibility, spatial structure and the latent variables on GA travelcard holdings. Hence, using a multivariate modeling approach helps to better determine the effects of the explanatory variables. Judging from the pseudo R^2, the univariate models achieve an explanatory power comparable to earlier studies in Switzerland (Kowald et al., 2017), whereas the joint modeling approach achieves a higher explanatory power. Moreover, it is important to note that excluding respondents without a drivers license does not change the results substantially (cf. Table A.11).

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

The results of the model draw a clear picture of how the different mobility tools are used. For example, as shown in the four models, accessibility to both population and employment has a substantial impact on the choice of mobility tools. The better a place is accessible, the less likely households are to own a car. In turn, residents of such areas own more season tickets for public transportation. The micro-accessibility of public transportation affects the choice of mobility tools in a similar way: Living in an area with a high micro-accessibility[10] (i.e. levels A or B) substantially increases the propensity to hold season tickets and car-sharing memberships. With respect to car-sharing, it is interesting to note that only the effect of the micro-accessibility of public transportation is significant, whereas the

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

	season ticket		car		car-sharing		GA travelcard	
	MVP	UVP	MVP	UVP	MVP	UVP	MVP	UVP
Age [y]	-0.046***	-0.051***	0.014***	0.014***	-0.009***	-0.010***	-0.048***	-0.033*
Agesq [$y^2/100$]	0.041***	0.046***					0.045***	0.033*
Male			0.263***	0.274***	0.116	0.124	0.155**	0.236**
University degree (or equivalent)			0.021*	0.003	0.165*	0.177*	0.053	0.106
log household size			-0.001	0.019	-0.034	-0.062		
log household income [kCHF] per $\sqrt{householdsize}$	0.072	0.081	0.343***	0.346***	-0.044	-0.031	0.081	0.040
Main accessibility	0.107***	0.110***	-0.053**	-0.055**	0.064	0.057	0.033	-0.068*
Comp. better accessibility by transit	0.037	0.033	-0.109***	-0.110***	0.083	0.090	0.043	0.028
Comp. better accessibility to employment	1.087***	1.051***	-0.784***	-0.766***	0.200	0.229	0.372	0.420
Living and working in city center(s)	0.526***	0.531***	0.000	0.000			0.359***	-0.012
Living and working an agglomeration			0.329***	0.307***				
Living and working in agglomeration or isolated city			0.634*	0.604*				
Living and/or working in a rural municipality			0.318***	0.300***				
PT-microaccessibility at least level B	0.135**	0.118*	-0.111*	-0.113*	0.205**	0.212*	0.029	-0.038
Distance to closest car-sharing station [km]					0.003	-0.002		
Domestic distance travelled [$100 km/day$]	0.160***	0.153***	0.029	0.000			0.306***	0.366***
PROINFRA	0.200***	0.208***	-0.076***	-0.077***	0.068	0.079	0.130**	-0.011
PROFEES	0.354***	0.358***	-0.343***	-0.343***	0.382***	0.386***	0.446***	0.352***
Indicator for 2010 census	0.170***	0.163***	-0.029	-0.032	0.064	0.064	0.033	-0.115
Constant	-0.825***	-0.712***	-0.197	-0.209	-2.174***	-2.126***	-1.434***	-0.209
Pseudo R^2	0.37†	0.17	0.37†	0.11	0.37†	0.13	0.37†	0.10
N	6939	6939	6939	6939	6939	6939	6939	6939

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

† Pseudo R^2 as calculated for the joint model

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

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

Furthermore, the model shows that a higher household income per capita increases the propensity to own a car or hold a GA travelcard (weakly significant). In addition, people of higher education were found to be more likely to own a car or car-sharing membership. A possible interpretation of this observation is that while a higher household income allows to invest more in mobility options, professions available for highly-educated workers often require flexible commuting or travel.

For car ownership, not only the level of accessibility, but also the spatial structure of the municipality has a significant effect. While car-ownership is lowest for people both working and living in the centers of larger cities, living or pursuing activities in the fringe of an agglomeration has a similar effect on car-ownership as rural areas. This probably reflects the usually car-centered development of such municipalities. Given the substantial structural differences among the five isolated cities, the corresponding effect is hard to interpret.

Another interesting observation is that a growing household size has a negative effect on car-ownership and car-sharing membership (although insignificant). For car-ownership, this seemingly contradicts earlier findings that household size has a positive effect on the number of vehicles per household (Scott and Axhausen, 2006; Potoglou and Susilo, 2008). However, in this analysis, the response variable is car availability (i.e. always having a car available) which likely decreases when a car is shared by more than one household member. In turn, car-sharing membership is less likely for larger households given that larger households are more likely to own a private vehicle covering also those use cases, a car-sharing vehicle would have been used for otherwise.

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

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

An important observation already at this stage is that the effect of the covariates discussed above on car-sharing membership is positively correlated to season ticket ownership, but negatively correlated with car-ownership.

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

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

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

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

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

A.7 CONCLUSIONS

The modeling approach presented above goes beyond earlier models by jointly addressing four different types of mobility tools and capturing the effect of attitudes on the individual alternatives. As presented in Table A.8, the model reveals that there indeed are significant and substantial correlations in the error terms of the four equations indicating that common unobserved effects are present, even after controlling for transport policy attitudes. Possible examples of such unobserved effects may be lifestyle attributes or the structure of social networks. However, independent of the actual nature of the unobserved effects, this research shows that earlier approaches without joint estimation (e.g. Kowald et al. (2017)) can only provide the direction, but not the magnitude of the effects of the explanatory variables.

Another interesting observation is that there is a significant effect of the latent variables on the choice of all four mobility tools. Although the attitudes to a certain degree have to be considered as endogenous (Dobson et al., 1978), they do explain a substantial share of the choice behavior. Yet, the model may only be used to describe the current situation, but not to predict levels of mobility tool ownership for varying degrees of attitudes (Chorus and Kroesen, 2014). It is interesting to note that the effect of the two latent variables is similar for car-sharing membership and GA travelcard ownership in that the *PROINFRA* variable has no (highly) significant effect and in that the size of the significant effect of the *PROFEES* variable is similar. This is in contrast to season ticket ownership for which the effect of *PROINFRA* is significant and positive. Hence, car-sharing members share the idea of an enhanced regulation or taxation of car use, but do not demand higher investments into public transportation. Yet, it is unclear whether this is due to the fact that they already benefit from good conditions for public transportation or whether this reflects a general tendency to lower government spending. Either way, the results of this research show that the effect of individual attitudes should not be neglected when describing mobility tool ownership.

The results further confirm the important role of accessibilities in shaping travel behavior (Ewing and Cervero, 2010). Although often described by spatial structure (Simma and Axhausen, 2001; Scott and Axhausen, 2006), population density (Kowald et al., 2017) or distance to the city center (Yamamoto, 2009), earlier studies have consistently found lower levels of car-ownership and increased use of public transportation for people living in urban centers. However, it was also shown that accessibility (i.e. travel times to attractions) is not the only determinant, but has to be regarded in conjunction with the micro-accessibility (i.e. frequency) of public transportation as well as the spatial structure of the municipality. In particular, the results confirm earlier findings that car-sharing adoption does not depend on densities or accessibilities, but on the micro-accessibility of public transportation (Celsor and Millard-Ball, 2007; Stillwater et al., 2009). However, the effective distance to the next available car-sharing station has no significant effect. This clearly indicates that station-based car-sharing is not used for daily travel, but to complement a public transportation lifestyle.

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

With respect to the general spatial and individual characteristics governing car-sharing adoption, this research allows to confirm many results of earlier research. Also here, car-sharing was found to be favored by young and highly educated customers living in small households in an area which is well-connected by public transportation (Celsor and Millard-Ball, 2007; Stillwater et al., 2009). However, in contrast to earlier findings, a higher household income per capita does not have a significant effect on car-sharing membership.

Moreover, it should be noted that including land-use variables as mere exogenous variables is not accurate given that also the choice of a home location may be in itself affected by preferences for certain mobility tools (Pinjari et al., 2008; van Wee, 2009; Cao et al., 2009).

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

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

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

APPENDIX

ACKNOWLEDGEMENTS

This research is part of a Swiss National Fund project (National Research Program 71: Managing Energy Consumption, project number 407140_153807) and was supported by the ETH Research Grant ETH-04 15-1. The help of

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

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

Nathalie Picard and Michel Bierlaire in designing and implementing the modelling framework is greatly appreciated. We also thank the two anonymous reviewers for their helpful comments.

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

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

† Pseudo R^2 as calculated for the joint model

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

B

COMPARING CAR-SHARING SCHEMES IN SWITZERLAND: USER GROUPS AND USAGE PATTERNS

This paper has been published as: Becker, H., F. Ciari and K. W. Axhausen (2017a) Comparing car-sharing schemes in Switzerland: User groups and usage patterns, *Transportation Research Part A*, **97**, 17–29

ABSTRACT

Free-floating car-sharing schemes operate without fixed car-sharing stations, ahead reservations or return-trip requirements. Providing fast and convenient motorization, they attract both public transportation users and (former) car-owners. However, given their highly flexible nature and different pricing structures, previous findings on user groups and environmental impact of station-based car-sharing may not be easily transferable. Therefore, this research uses survey data to compare user groups and usage patterns of a free-floating and station-based car-sharing service both operating in the city of Basel, Switzerland. The findings suggest, that the schemes indeed attract different user groups and are also used differently. Moreover, we see, that car-sharing membership is governed by other factors than car-sharing activity.

CONTRIBUTIONS

The survey was designed by H. Becker and F. Ciari. H. Becker conducted the data collection, developed the concept of the paper and performed the data analysis and interpretation. F. Ciari and K.W. Axhausen supervised the work and provided feedback at various stages.

B.1 INTRODUCTION

Since its first implementation in the late 1940s, car-sharing has long been a niche service, unable to attract a substantial share of the urban population. This was due to both the inflexibility of car-sharing schemes themselves and the social importance of car ownership. In recent years, the game has changed; modern information technology has allowed the schemes to become more user-friendly and social trends favoring sharing over ownership support their adoption.

One of the latest additions to the car-sharing market is free-floating car-sharing. Instead of relying on designated car-sharing stations, it allows customers to pick up and drop off the vehicle anywhere within a city-wide service area. Through this innovation, it removed the obstacles of station-based car-sharing, such as required advance reservations and restrictions on a set of pre-defined stations as trip origins and destinations.

Given these structural differences between the two service types, knowledge about user groups and environmental impact of station-based car-sharing may not be directly transferrable to free-floating car-sharing. However, few empirical studies have explored user groups and usage patterns of free-floating car-sharing (Kopp et al., 2013; Schmöller et al., 2015). Estimating the environmental impact of the new service has proven even more difficult. Offering a convenient and fast new form of urban mobility, free-floating car-sharing attracts both (former) car owners and transit users. It is, however, still unclear how the segment's growth affects overall travel behavior (Seattle Department of Transportation, 2014).

The introduction of free-floating car-sharing in Basel allows investigation of the usage and impacts of two different forms of car-sharing in a Swiss context for the first time. Using new data, this research allows direct comparison of user groups and usage patterns for a station-based and a free-floating car-sharing scheme operating in the same city. The results are a first step towards better understanding the specific market niche of free-floating car-sharing.

The remainder of this paper is structured as follows: Section 2 provides a short overview of relevant scientific literature and Section 3 describes the methodology of this study, including details about response behavior.

The results of this study are then presented in Section 4, followed by an attempt to model adoption of the two schemes in Section 5. Sections 6 and 7 conclude with a discussion of research results.

B.2 BACKGROUND

The roots of today's car-sharing schemes can be traced back to the late 1940s, when the first schemes were conceived to share a useful, yet expensive, asset - the car. As the first implementation of a car-sharing scheme, the Sefage program in Zurich was established in 1948 (Harms and Truffer, 1998). However, in an era of fast and ever-cheaper private motorization beginning in the 1950s, car-sharing lacked attractiveness. It was only in the early 1990s that rising fuel prices and congested road networks paved the way for a successful revival of the idea of car-sharing. Technology has been a key element in expanding this new potential by providing user-friendly systems and efficient allocation strategies, even leading to the development of new structures like peer-to-peer car-sharing, or free-floating car-sharing.

Following its expansion, car-sharing also started to attract the attention of researchers 20 years ago (Millard-Ball et al., 2005). While most of the research addressed traditional station-based car-sharing services, focus has recently shifted towards more advanced forms like one-way car-sharing (Shaheen et al., 2015). Today, research has reached consensus on several issues: for station-based car-sharing, it is widely accepted that the most suitable markets are dense urban areas with good public transport (Stillwater et al., 2009; Grasset and Morency, 2010) and that the prototype user is relatively young, affluent and well-educated (Burkhardt and Millard-Ball, 2006). As far as the impact of car-sharing on the transportation system, researchers were able to confirm several positive impacts including less vehicle travel and lower emissions (Cervero and Tsai, 2004; Martin and Shaheen, 2011b), reducing the need for parking (Millard-Ball et al., 2005; Shaheen et al., 2010) and promotion of public transportation use and active modes (Sioui et al., 2013).

Early predictions of car-sharing demand and diffusion levels, however, proved overly optimistic; for example, an early study in Austria estimated a potential market share of 9% (Steininger et al., 1996a) and a Swiss study predicted a potential of 600 000 customers for the Mobility Switzerland service (Muheim and Reinhardt, 1999). Both were off by more than a factor of five. In contrast, a more recent approach that estimated market potential based on census data was able to accurately model and predict station-based car-sharing membership (Ciari et al., 2015b).

Recently, research has extended its scope to one of the newest forms of car-sharing: free-floating car-sharing (Shaheen et al., 2015). Similar to station-based car-sharing, free-floating car-sharing attracts mostly young customers living in small households (Schmöller et al., 2015). Passive GPS-tracking also revealed that free-floating car-sharing members are characterized by higher trip frequencies and a more multimodal travel behavior than non-members (Kopp et al., 2015). Using a simulation approach to understand free-floating car-sharing usage patterns and trip purposes at the user level, Ciari et al. Ciari et al. (2014) further predicted that, in contrast to station-based car-sharing, free-floating car-sharing would also be used for commuting and that trips with free-floating car-sharing generally would turn out to be shorter than trips made with station-based car-sharing.

Simulation indications were confirmed by insights from two major studies, the WiMobil study in Germany (BMW AG et al., 2016) and the Carplus survey in the United Kingdom (Steer Davies Gleave, 2016), both of which used surveys and GPS tracking (WiMobil only) to compare free-floating and station-based car-sharing schemes operating in the same city. In addition, the results of both studies imply that free-floating car-sharing attracts even younger and more numerous male customers and is used more regularly than station-based car-sharing. Moreover, a comparison between station-based one-way and round-trip car-sharing in France found that one-way car-sharers have a more negative perception of public transportation than round-trip members (6t, 2014).

However, the environmental impact of free-floating car-sharing is not fully understood. While early studies seemed to predict a significant reduction in car ownership and CO_2 emissions (Firnkorn and Müller, 2012) from free-floating car-sharing, the actual impact seems to be more complex as non-car-owners reduce bike, walk and public transit trips, while starting to use a (shared) car (Firnkorn, 2012). First reports from municipalities that introduced free-floating car-sharing were also ambivalent (Seattle Department of Transportation, 2014). A recent British study directly comparing station-based one-way car-sharing to round-trip car-sharing confirmed that the structural differences between the services imply different usage patterns. In particular, they found that round-trip car-sharing has a far more positive impact on the transport system because it is used to complement public transit, whereas point-to-point car-sharing is used in parallel to public transportation and therefore has a less definitive impact on the transportation system (Le Vine et al., 2014). This is supported by evidence from various surveys in Europe and North America (BMW AG et al., 2016; Steer Davies Gleave, 2016; 6t, 2014; Martin and Shaheen, 2016) indicating that free-floating car-sharing induces a reduction in car-ownership and vehicle miles travelled: however, to a lesser extent than station-based round-trip car-sharing.

Despite its lower overall environmental impact, one-way car-sharing appears to cause substantial changes in its members' activity patterns; for example, non-car-owning members of a point-to-point car-sharing scheme were found to shop less frequently for groceries, to visit fewer distinct food shops and to spend less total time traveling for grocery shopping purposes (Le Vine et al., 2014). Similar impacts can be expected for free-floating car-sharing. In addition, previous research suggests that the usage of free-floating car-sharing is not stable, but dependent on weather conditions (Schmöller et al., 2015) or pricing structures (Ciari et al., 2015a).

As a next step to better understand the characteristics of free-floating car-sharing, this research uses new data to compare user groups and usage patterns with those of station-based car-sharing.

B.2.1 *Car-sharing schemes in Basel*

At this point in our research, Basel is the only city in Switzerland with both station-based and free-floating car-sharing schemes.

The station-based car-sharing scheme currently operating in Switzerland dates back to 1987. Available not only in larger cities like Basel, but also in smaller towns and villages, it is probably the only scheme worldwide offering a seamless system serving a whole country. It offers access to almost 3 000 vehicles of various types at 1 500 car-sharing stations. Members can either: buy a share of the cooperative (one-time investment of 1 250 CHF of which 1 000 CHF is refundable upon exit; 1.00 CHF = 0.68 USD at purchasing power parity, OECD 2015), or subscribe to the service for an annual fee of 200 to 300 CHF. The membership fee can be substantially reduced to

CHF 25 for holders of a public transportation subscription, although these members pay higher rental fees. Rentals are charged both by the hour and by distance travelled (3 to 4 CHF/h plus 0.50 to 1.00 CHF/km, depending on the vehicle type and time of the day).

In August 2014, a free-floating car-sharing pilot program was launched in Basel, Switzerland. 120 cars of the type VW Up were distributed around the city. They can be located via a website or smartphone-app and reserved up to 15 minutes in advance. Customers must pay a small registration fee (25 CHF) upfront and then only pay on a per-use basis. The fare structure distinguishes between parking and driving time; customers are charged per minute (fares: 0.41 CHF/min driving and 0.24 CHF/min parking). At the end of the journey, the vehicle can be parked on any public parking spot within the service area, where it then becomes available for other members.

Although both the station-based round-trip car-sharing scheme and the free-floating car-sharing scheme are operated by the same company, they are run entirely separately from each other. As a consequence, customers wishing to use both schemes must register for each scheme separately.

B.3 METHODOLOGY AND DATA

The results of this paper are based on a survey of three different groups surveyed approximately one year after launch of the free-floating car-sharing scheme. The three groups considered for the survey are: members of the new free-floating car-sharing scheme, members of the conventional car-sharing scheme and drivers' license holders from a random sample of the local population. This way, the user group of the free-floating car-sharing service can be compared to both station-based car-sharing users and a representative control group.

For ease of notation, the conventional station-based round-trip car-sharing scheme in Basel will be referred to as 'station-based car-sharing' in the rest of the paper.

B.3.1 *Recruitment and data acquisition*

In total, 1 104 free-floating members, 1 616 station-based members and 3 094 members of the random sample were invited to take part in the survey. Address lists of car-sharing members were made available by the operator; surface-mail addresses for the local population random sample were provided by the Cantonal Statistical Office of Basel-Stadt. The random sample was drawn from the population of the Canton of Basel-Stadt above legal driving age.

Each of the three participant groups was provided with a dedicated questionnaire asking their socio-demographic background, as well as information on their general travel behavior and their last car-sharing ride (where applicable). Car-sharing members were recruited via e-mail and were able to access an online-survey using personalized links, while members of the control group received the survey in pencil-and-paper-format via surface mail, including a reply-paid envelope. No incentive was promised for returning a completed questionnaire.

Invitations to the study were sent to the respondents in weekly cycles in November 2015. Reminders were sent out to all car-sharing members who failed to respond within two weeks.

To predict the response rates of this survey, the method proposed by Axhausen et al. Axhausen et al. (2015b) was used. According to those specifications, response burdens of the questionnaires were calculated as 178 points (free-floating members), 173 points (station-based members) and 135 (control group). Axhausen et al. Axhausen et al. (2015b) suggest that, for such simple surveys, a response rate between 20% and 40% can be expected. Although response rates for the questionnaires of car-sharing members were well within the expected range, the control groups fell off a bit. This may be explained by the fact that both car-sharing groups could be regarded as pre-recruited, given that they were contacted on behalf of a service to which they already belonged. The highest response rate was registered for the free-floating car-sharing members, possibly indicating a higher level of identification with the service.

	free-floating	station-based	control group
Invitations sent	1 104	1 616	3 094
Surveys completed	412	515	553
Respondents with drivers license	412	515	432
Response rate of the eligible	37.3%	31.9%	13.8%

Table B.1: Response rates by group

B.3.2 *Data Preparation*

Only completed questionnaires were considered for the analysis. Further, responses from car-sharing members who completed the survey in less than seven minutes (a third of the average time) were excluded. In addition, unreasonable answers were identified on a per-question basis (e.g. year of birth before 1900). Finally, out of 1 599 returned questionnaires, 1 480 were available for the analysis.

Average response time for the online survey was slightly less than 15 minutes. Given the lower response burden of the paper-and-pencil questionnaire, an even lower response time could be assumed for the control group. Given such a compact survey design, fatigue effects were not expected.

For the control group, only the subgroup of driver's license owners was considered. Although this limits the comparability of car-sharing members with the general population, it reflects the fact that only driver's license holders are potential car-sharing members.

To check for selection bias, the car-sharing member response groups were compared to age and gender information available from the address lists. To enhance the representativeness of the results, sample weights by gender and age group (in five-year steps) were applied. Because likelihood of participation in such a survey is a function of education (Armoogrum and Madre, 1996), responses from the control group were also weighted by level of education. Since no marginal distribution of education level was available for either car-sharing group, weighting according to this variable was not possible. However, given the higher response rate among car-sharing members, sample bias was expected to be much weaker than that for the control group. It was assumed that no further attributes had an effect on survey participation; the weighted samples can be deemed representative for their respective populations.

To test this assumption for the control group, their distribution of household size, available household income and car ownership was compared to the results of the Swiss transportation micro census (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012) for the city of Basel. While there was an only marginal and insignificant difference in average household size ($\mu = 2.39$, $\sigma = 0.06$ for control group vs. $\mu = 2.46$, $\sigma = 0.02$ for micro census) and car ownership ($\mu = 0.73$, $\sigma = 0.03$ for control group vs. $\mu = 0.78$, $\sigma = 0.03$ for micro census), the difference in available household income was significant, although not substantial ($\mu = 6\,669$ CHF, $\sigma = 146$ CHF for control group vs. $\mu = 7\,213$ CHF, $\sigma = 74$ CHF for micro census). Therefore, the weighted sample of the control group was assumed to be a valid representation of the Basel population.

Finally, given that all respondents from the control group lived within the service area of both car-sharing schemes and given that the distribution of the control group respondents' home locations showed only minor deviations from those of the car-sharing members, spatial effects were also omitted.

B.4 SURVEY RESULTS

All three survey groups were treated separately, so that the characteristics of the free-floating car-sharing users could be compared to both the station-based car-sharing users and the control group. In this section, the most important results of the survey are summarized. Although further information was available, some of it had to be withheld to protect the operator's commercial interests.

B.4.1 *Member Profiles*

B.4.1.1 *Socio-Demographics*

70% of the free-floating car-sharing members in Basel are male, compared to 60% for the station-based car-sharing service; men are substantially over-represented among car-sharing members, compared to their share of 55% in the control group of drivers' license holders. Yet, the difference is only significant for free-floating members ($p < 0.001$), but not for station-based members ($p = 0.647$).

Relevant research literature has already documented that station-based car-sharing attracts customers several years younger than the average adult population (Millard-Ball et al., 2005). Similar to the gender distribution described above, the average age of free-floating car-sharing members was found to be even lower than that of the station-based car-sharing service. In fact, half of the free-floating car-sharing scheme members were less than 36 years old (median age in the control group was 47 years). Moreover, the differences between the mean ages of all three groups are highly significant ($p < 0.001$).

Differences in the highest educational degree were also apparent. 70% of the members of the free-floating car-sharing scheme and 75% of the station-based members held a university degree (or equivalent) compared to 37% of the control group. The differences are significant for both groups ($p_{ff-cg} < 0.001$, $p_{sb-cg} < 0.001$).

The age differences were reflected in employment status; 80% of the members of both car-sharing schemes were part of the economically active population, compared with 70% of the control group members ($N_{ff} = 412$, $N_{sb} = 512$, $N_{control} = 432$). Self-employed workers and students were significantly over-represented among station-based car-sharing members. Only 3% of the car-sharing members were retirees.

Regarding household size and income, free-floating car-sharing members' average was slightly above the control group and members of the station-based car-sharing slightly below; these differences were not substantial.

B.4.1.2 *Attitudes*

To explore the role of attitudes as they appear to affect car-sharing membership, respondents were presented with different statements, following an approach already used in earlier studies (e.g. (Millard-Ball et al., 2005)). They were asked to state their agreement on a 5-point Likert Scale. The responses are given in Figure B.1 While there were no substantial differences in attitudes towards environmental issues and social responsibility,

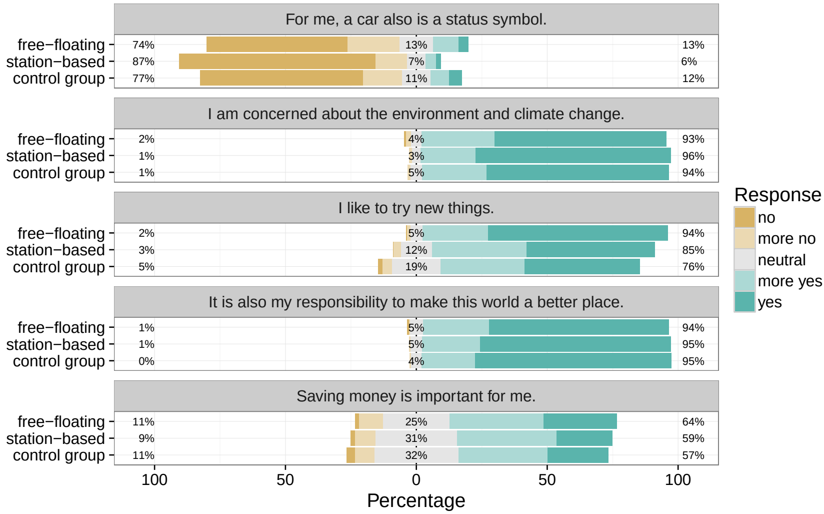


FIGURE B.1: Responses towards attitudinal questions.

differences were observable in three other dimensions; 13% of free-floating car-sharing members agreed that a private car still serves as status symbol. Thus, agreement was significantly higher than among the station-based car-sharing group (6%, $p < 0.001$), as well as among the control group (12%, $p = 0.011$; $N_{ff} = 408$, $N_{sb} = 508$, $N_{control} = 425$). Moreover, 64% of the free-floating car-sharing members considered it important to save money; agreement among station-based members (60%, $p = 0.023$) and control group members (57%, $p = 0.018$) was slightly lower ($N_{ff} = 410$, $N_{sb} = 511$, $N_{control} = 420$). Larger differences were observed about the statement "I like to try new things"; 95% of free-floating car-sharers and 85% of station-based car-sharers agreed, compared to 76% agreement in the control group ($p_{ff-sb} < 0.001$, $p_{ff-cg} < 0.001$, $N_{ff} = 409$, $N_{sb} = 513$, $N_{control} = 420$).

B.4.1.3 *Travel Behavior*

As suggested by the literature, car-sharing member households were found to be much less car-oriented than the control group. In particular, more than 90% of the members of the station-based car-sharing service and 73% of the free-floating members lived in car-free households. Differences in average number of cars per household are also highly significant ($p < 0.001$

for all three combinations of groups). Car-sharing households were, in turn, significantly better equipped with bicycles (c.f. Table B.2).

A reverse situation was observed in season ticket holdings ($N_{ff} = 412$, $N_{sb} = 515$, $N_{control} = 432$). Notably, the share of GA travel card holders (granting year-long public transport use across Switzerland) was almost twice as high among free-floating (26%) and station-based (28%) car-sharing members as in the control group (14%, $p < 0.001$). Differences in local season tickets were less substantial: (free-floating 29%, station-based 23%, control group 28%).

Differences in mobility tool ownership were further reflected in the respondents' mode use. While 50% of the control group members drove an owned car at least once a week, this was only true for 14% of the free-floating members and 4% of the station-based members ($N_{ff} = 256$, $N_{sb} = 314$, $N_{control} = 224$). In turn, car-sharers used their bike and public transportation (particularly trains) more often than the control group.

	0	1	2	3+
Cars				
free-floating	73.2%	22.4%	3.2%	1.3%
station-based	91.1%	8.0%	0.7%	0.1%
control group	38.5%	51.1%	9.6%	0.9%
Motorbikes				
free-floating	84.0%	14.4%	1.0%	0.6%
station-based	91.4%	8.0%	0.5%	0.1%
control group	80.7%	13.7%	4.6%	1.0%
Bikes				
free-floating	7.6%	22.9%	29.6%	39.9%
station-based	5.3%	22.4%	28.8%	43.5%
control group	14.7%	23.0%	26.8%	35.4%

Table B.2: Vehicle Ownership ($N_{ff} = 412$, $N_{sb} = 513$, $N_{cg} = 432$)

B.4.2 *Usage Patterns*

Due to their distinct designs, free-floating and station-based car-sharing would be expected to serve different markets. To capture this difference, car-sharing members were asked to provide details about their most recent car-sharing ride. To allow conclusions for the whole system, responses were additionally weighted by frequency of car-sharing use.

As illustrated in Figure B.2, most of the trips undertaken with a station-based car-sharing vehicle were shopping or leisure trips, or trips where the customer had large items to carry. In contrast, the free-floating car-sharing service was employed for multiple purposes. In particular, there was also substantial usage for commuting and airport transfers.

When asked why they had used car-sharing for their last car-sharing ride, 76% of the free-floating members stated that car-sharing was the fastest option. Members of the station-based service, however, also cited goods to carry as a main reason to use car-sharing (40%). In fact, 50% of the station-based members carried large items on their last car-sharing ride, compared to 23% of the free-floating members ($p < 0.001$, $N_{ff} = 155$, $N_{sb} = 201$).

Not only are station-based car-sharing vehicles more likely to be loaded with goods, they also have more passengers on board. Whereas 64% of the free-floating trips ($N_{ff} = 148$) were conducted by a single driver, 58% of the station-based cars ($N_{sb} = 195$) had two or more people on board. Consequently, the average occupancy was significantly higher for station-based car-sharing (1.8) than for the free-floating service (1.4, $p < 0.001$).

Moreover, the different nature of the car-sharing schemes is reflected in the members' planning horizons. When they were asked how long before the actual trip they had planned to use car-sharing (which can be long before the booking step), 62% of the station-based car-sharing members responded that they had planned their last car-sharing ride at least one day ahead ($N_{sb} = 506$). In contrast, 72% of free-floating members planned their car-sharing trip less than one hour in advance ($N_{ff} = 409$). Therefore, station-based car-sharing appears to be more planned travel behavior, while free-floating car-sharing is, by design, used spontaneously.

To better understand how the different kinds of car-sharing are used, re-

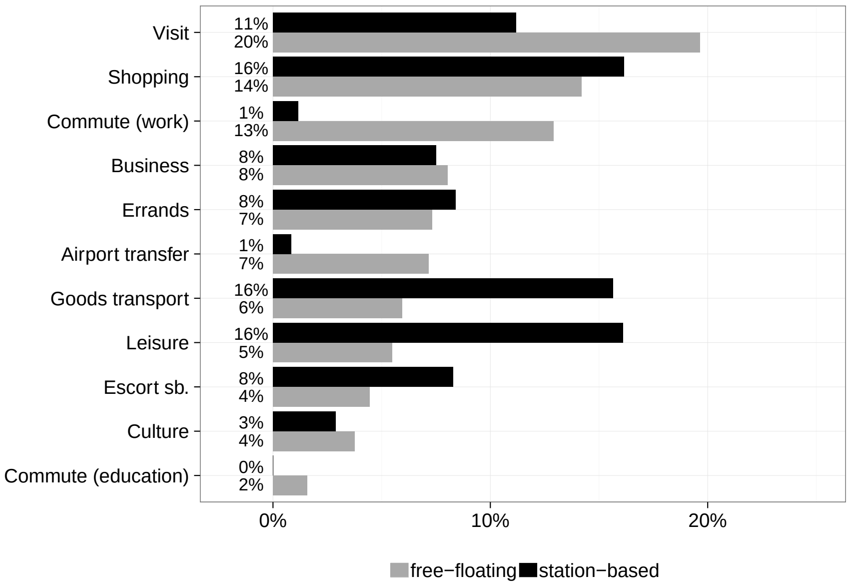


FIGURE B.2: Main purpose of the last car-sharing ride ($N_{free-floating} = 412$, $N_{station-based} = 515$). Rest to 100% is "other".

spondents were asked whether they had experienced lack of availability for the car-sharing service (i.e. they wanted to use car-sharing, but no vehicle was available within an acceptable distance). Figure B.3 shows how respondents reacted to this situation. 56% of the station-based trips were postponed, or even cancelled, while 53% of the free-floating car-sharing trips were replaced by public transportation. This indicates that station-based car-sharing is mostly used for discretionary trips actually requiring a car, whereas free-floating car-sharing mostly serves indispensable trips that happen to be faster by car.

B.4.3 *Travel Behaviour Impact*

By providing a flexible alternative to a private vehicle, car-sharing has a direct impact on its members' travel behavior (Cervero et al., 2007). The survey data allows a first insight into the different effects of car-sharing schemes.

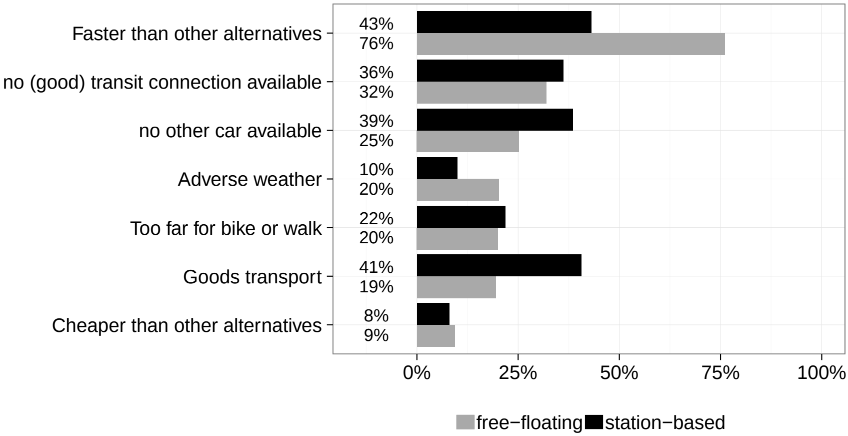


FIGURE B.3: Reason for using car-sharing for the last car-sharing ride ($N_{free-floating} = 384$, $N_{station-based} = 472$). Multiple responses permitted.

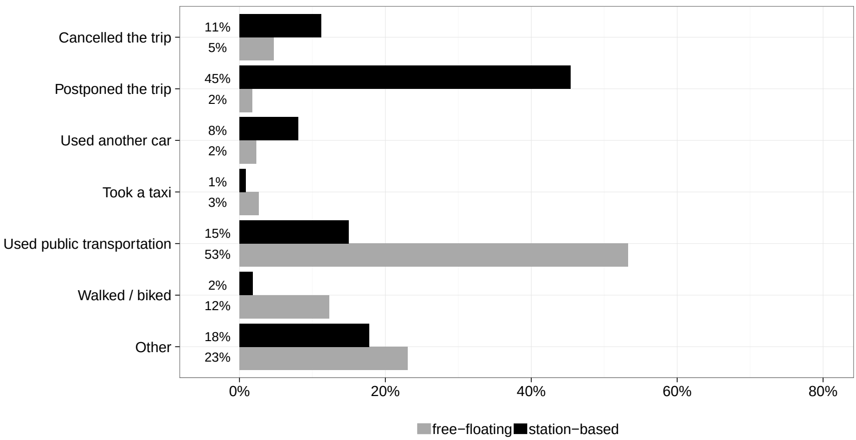


FIGURE B.4: Reaction when no car-sharing vehicle was available ($N_{free-floating} = 329$, $N_{station-based} = 420$).

B.4.3.1 *Car Ownership*

Car-sharing enables households to reduce their private vehicle holdings and turn towards a transit-oriented lifestyle, a major impact. In the survey, 8% of free-floating car-sharing members and 19% of the station-based car-sharing members stated that they would buy a car, if the respective car-sharing scheme did not exist ($p < 0.001$, $N_{ff} = 412$, $N_{sb} = 513$). Although such hypothetical scenarios (as well as retrospective questions) do not allow a full quantification of the impact of such systems, it is safe to assume that both kinds of car-sharing contribute to lower private vehicle holdings. Moreover, the impact of station-based car-sharing appears to be stronger than the impact of free-floating car-sharing - thus confirming indications from earlier research (BMW AG et al., 2016; Steer Davies Gleave, 2016; 6t, 2014; Martin and Shaheen, 2016).

B.4.3.2 *Mode Choice*

Figure B.5 shows which transport modes the respondents use - more or less often – given their car-sharing membership. The figure reveals a substantial difference in the schemes' impact on travel behavior. While station-based car-sharing generally encouraged the use of public and non-motorized transportation among most of its members, more free-floating car-sharing members have also reduced their use of those modes. Moreover, in an interesting paradox, a similar number of free-floating car-sharing members have increased and decreased their car use. In contrast, the trend clearly indicates a reduction in car use among station-based car-sharers.

It is important to note that those qualitative changes in mode use alone do not permit any conclusions about the environmental impact of the different car sharing schemes. Only quantitative data on actual changes in individual mode use would allow estimation of a net effect on mode choice (Seattle Department of Transportation, 2014).

B.5 UNDERSTANDING ADOPTION

Car-sharing adoption can be described in two variables: membership and frequency of use. Since the latter can only be observed for actual car-sharing members, those observations may be biased by a selection effect, because car-sharing membership is more frequent among certain socio-demographic groups than for others. Therefore, a Heckman sample selec-

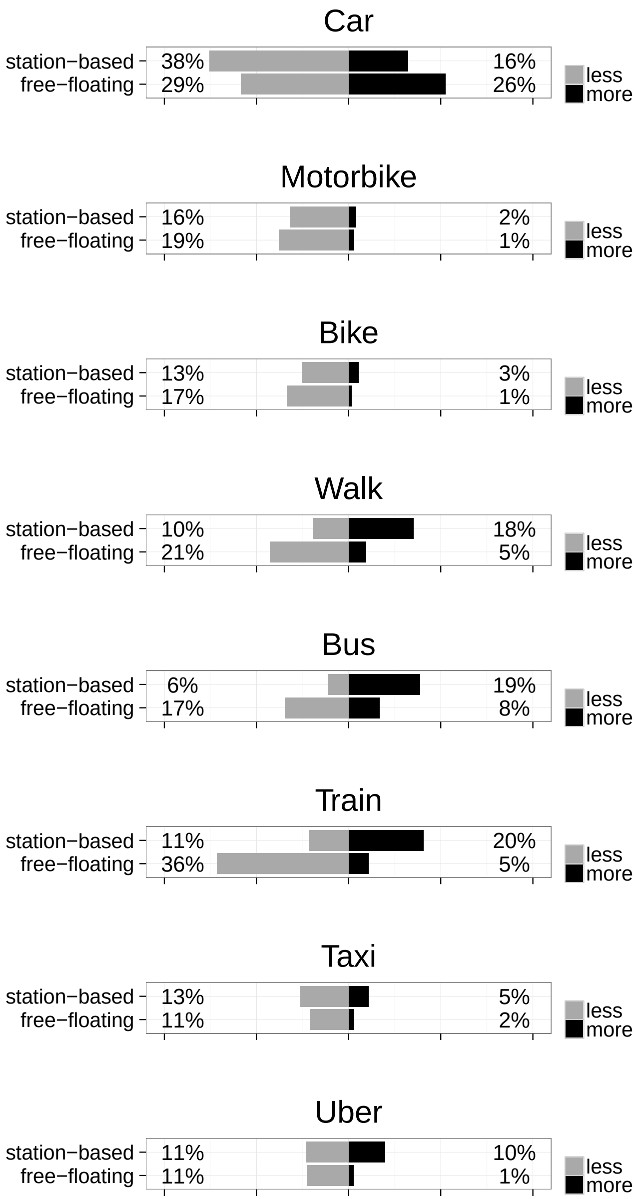


FIGURE B.5: Perceived change in mode use through the car-sharing membership ($N_{free-floating} = 337$, $N_{station-based} = 380$). Rest to 100%: "no change".

tion model was used to describe both membership and use in an unbiased way (Heckman, 1979). The Heckman sample selection model assumes that, for an underlying regression relationship

$$y_j = \mathbf{x_j}\mathbf{fi} + u_{1j}$$

the dependent variable for observation j is only observed if

$$z_j\gamma + u_{2j} > 0$$

with $u_1 \sim N(0,\sigma)$, $u_2 \sim N(0,1)$ and $corr(u_1,u_2) = \rho$. The first equation is referred to as *regression equation*, while the second equation is called *selection equation*. In the Heckman approach, sample selection is treated as a form of omitted-variable bias and is addressed by including the inverse mills ratio evaluated at the selection equation into the regression equation.

The data for this model was obtained from the questionnaires and weighted according to age, gender (all groups) and education (control group only). For each model, responses from the control group and the respective member group were used. In a second step, the model allowed an estimation of the customer potential for free-floating car-sharing in other Swiss cities.

B.5.1 *Modeling Membership and Use*

In the selection equation, the effect of various socio-demographic factors on active car-sharing membership was modeled using a binomial probit model; "active" is a member with at least one rental within the last 12 months. In the main regression, frequency of use was modeled in an ordinal probit approach according to the levels in the questionnaires (c.f. Table B.3). Since there were almost no observations of free-floating car-sharing users without a recent ride, only three levels of use were modeled for free-floating car-sharing, compared to four levels for station-based car sharing (compare Table B.4).

The highly significant Wald test indicates a good model fit for both models, but surprisingly, the insignificant ρ indicates that the null-hypothesis, stating that errors of selection and outcome equation are uncorrelated, cannot be rejected. Although using a full-information maximum likelihood estimator would be preferable in this case, Heckman's two-step estimator was used for this research due to its lower complexity. To test validity, the two stages were also estimated separately, which confirmed that model

Variable	Type	Description
Frequency of Use	factor	Stated frequency of use of the respective car-sharing service; levels are *(almost) never, rarely, regular (monthly or weekly), (almost) daily*
Active Membership	factor	Member of the scheme and at least one rental within the last 12 months
Age	numeric	
Male	factor	
University degree	factor	Respondent holds a degree from a university or university of applied sciences
Normalized income [kCHF]	numeric	Gross household income divided by adult household members
Fulltime worker	factor	Workload of more than 36 h/week.
Parttime worker	factor	Workload of less than 20 h/week
Occupation type: self-employed	factor	
Occupation type: retiree	factor	
GA travelcard	factor	Public transportation subscription allowing unlimited use of public transportation throughout Switzerland
Car-free household	factor	Respondent's household does not own private car
# cars per adults in household	numeric	Number of cars divided by number of adults in the respondent's household
Transit quality zone A	factor	Home location in transit service quality zone A as defined in the Swiss standard SN 640 290; represents the highest level of transit connectivity and requires a maximum departure interval of < 5 min per main load direction at rail stops in a 500 m perimeter
City center	numeric	Home location in the center municipality of the respective agglomeration
Station-based member	factor	Respondent stated to also be member of the station-based car-sharing service

TABLE B.3: List of Attributes

	free-floating			station-based		
	Coef.		s.e.	Coef.		s.e.
Frequency of use						
Age				-0.009		(0.006)
Male	0.395	**	(0.178)	0.140		(0.134)
Normalized income [CHF]	0.040		(0.028)			
Fulltime worker				0.545	***	(0.135)
Occupation type: self-employed				0.488	**	(0.190)
Occupation type: retiree	-0.854	**	(0.369)	0.531	*	(0.291)
GA travelcard	-0.349	**	(0.146)	-0.277	*	(0.141)
Transit zone A	-0.233		(0.150)			
Car-free household	0.539	***	(0.178)	0.764	***	(0.285)
Station-based member	-0.477	***	(0.169)			
Active Membership						
Age	-0.019	***	(0.005)			
Male	0.484	***	(0.109)			
University Degree	0.675	***	(0.121)	0.919	***	(0.109)
Normalized income [CHF]	0.042	*	(0.024)	0.034		(0.021)
Parttime worker	0.407	***	(0.124)	0.377	***	(0.112)
Occupation type: self-employed				0.356	**	(0.160)
Occupation type: retiree	-0.566	**	(0.230)	-1.017	***	(0.141)
GA travelcard	0.255	**	(0.121)	0.228	**	(0.110)
# cars per adult in household	-0.645	***	(0.167)	-1.869	***	(0.219)
Transit zone A	-0.571	***	(0.133)			
City center	-0.251		(0.180)			
City center $\times$ transit zone A	-0.514	***	(0.142)			
Station-based member	0.771	***	(0.123)			
Constant	-0.602	**	(0.286)	-0.503	***	(0.137)
cut1	0.328		(0.450)	-2.693	***	(0.558)
cut2	2.887	***	(0.467)	0.572		(0.545)
cut3				3.422	***	(0.697)
athrho	-0.036		(0.230)	-0.064		(0.247)
N	882			974		
null log pseudolikelihood	-896.93			-1 027.14		
log pseudolikelihood	-708.22			-810.71		
Wald χ^2	33.27	***		38.12	***	
ρ	-0.036		(0.247)	0.064		(0.246)

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

TABLE B.4: Ordered Probit Model to describe Car-Sharing Adoption.

results were unbiased. Additionally, results of the selection equation for station-based car-sharing were in line with previous research on modeling station-based car-sharing membership based on data from the Swiss national travel survey from 2010 (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012; Ciari et al., 2015b).

The *selection equation* reveals similarities and differences in the two schemes' customer bases. While both schemes disproportionately attract transit-oriented university graduates living in car-free households as members, an inferior transit accessibility at the respondent's home location is also a substantial positive predictor for free-floating car-sharing membership, but irrelevant for station-based car-sharing membership. Moreover, membership in the station-based scheme seems to depend more on the life-cycle stage, whereas free-floating car-sharing is most appealing to young men. In addition, membership in the station-based car-sharing scheme has a significant and substantial positive effect on membership in the free-floating car-sharing scheme, which can partially be explained by the fact that members of the station-based car sharing scheme received a special advertisement through newsletters and were offered a reduced (or waived) registration fee for signup.

Observing the signs and significance levels of the predictors in the *regression equation*, it quickly becomes clear that car-sharing activity is governed by different factors than membership for both free-floating and station-based car-sharing. As expected, members from car-free households are significantly more active car-sharers. Moreover, a GA travel card has a weakly significant negative effect on car-sharing use. In addition, frequency of use of station-based car-sharing is governed by its members' employment status, whereas free-floating car-sharing is used most by young men with a higher income. Like the GA travel card, a university degree - a significant and substantial predictor for membership - was not found to have any significant effect on the frequency of use. In addition, station-based car-sharing membership has a negative effect on free-floating car-sharing use.

For the use of station-based car-sharing, the distance to the closest sharing station was not significant in any model, which is not surprising given that car-sharing stations are available in a relatively fine grid throughout the country. In fact, for the household locations of the study's respondents (including the control group), average distance to the closest car-sharing station was found to be 300 m.

For both services, the cut between daily and regular users is much more significant than between rare and regular users. In the model for station-based car-sharing, the cut between non-users and rare users is also significant and substantial, indicating, that there are three clusters of car-sharing users: non-users, occasional users and daily users.

B.5.2 *Predicting Customer Potential for free-floating Car-Sharing*

The free-floating car-sharing project in Basel is the first implementation of such a scheme in Switzerland. The results of the above model can thus be used to predict membership potential for free-floating car-sharing in other Swiss cities. To that end, data from the Swiss national travel survey 2010 (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012) was used for the five largest agglomerations in Switzerland: Zurich, Geneva, Basel, Berne and Lausanne. For each of the respondents holding a driver's license, the probability of car-sharing membership and user type was predicted. The individual probabilities were then been projected onto each city's population according to the probability weights assigned to each respondent.

The model suggests a market share between 6% and 12% of the population with driver's license in the large agglomerations (c.f. Table B.5). Most interestingly, the model suggests, that the prospects of free-floating car-sharing are less promising in the French-speaking part than in the German-speaking part of Switzerland. According to the model, Geneva and Berne offer a customer basis similar to that in Basel. However, Zurich offers - by far - the highest membership potential and is therefore likely to be the best case for a further expansion of free-floating car-sharing in Switzerland.

It is important to note that, while prediction error is quite low, level of prediction accuracy is unclear. This is largely because the model is mostly based on socio-demographic attributes and does not include information about individual attitudes, local geography, or the transport system (e.g. parking situation, reliability of public transportation), or special sources of demand such as airports or the United Nations headquarters in Geneva. Therefore, estimates presented in this chapter can serve only as rough es-

	Potential members	Standard Error	Share of driving population
Berne	10 095	483	11.7%
Zurich	27 739	927	10.7%
Basel	8 810	472	8.6%
Lausanne	6 517	463	7.7%
Geneva	8 259	348	6.5%

TABLE B.5: Membership potential

timates of free-floating car-sharing demand. Furthermore, the viability of a free-floating car-sharing scheme may also be affected by spatio-temporal distribution of travel demand, as well as cities' different sizes and densities.

B.6 DISCUSSION

Results from the questionnaires largely confirm and extend findings from other studies on both station-based and free-floating car-sharing. For example, overall results confirm that both schemes mainly attract younger and highly educated people living in households with few private cars (Burkhardt and Millard-Ball, 2006; Firnkorn and Müller, 2012; BMW AG et al., 2016). However, the model presented in Table B.4 highlights important differences; while station-based car-sharing seems to be adopted mainly by self-employed workers who appreciate the flexibility of using a car when needed, free-floating car-sharing thrives among young men with higher incomes, whose home location is not optimally served by public transportation. Especially the latter point is in line with earlier findings on an ambivalent relationship between public transportation accessibility and station-based car-sharing (Stillwater et al., 2009) and indicates that free-floating car-sharing fills a service gap left by public transportation.

Originally, car-sharing members were believed to hold particularly environmentally friendly attitudes (Burkhardt and Millard-Ball, 2006). However, more recent studies no longer see such a connection (6t, 2014). This research also revealed that neither of the two car-sharing groups is distinguished by particularly environmentally friendly convictions. Instead, the results seen in Figure B.1 imply that more openness to new services and societal developments correlates with car-sharing membership. However, this observation does not exclude a positive environmental impact of the two services, given that a significant share of members of both schemes report a reduction in their private vehicle ownership.

Results also suggest that the two car-sharing schemes are not only used by different customers, but also in different ways; station-based car-sharing is mostly used in situations actually requiring a car (c.f. Figure B.4), free-floating car-sharing is used when it helps save time compared to other alternatives (c.f. Figure B.3) - an effect which also appears in the WiMobil study (BMW AG et al., 2016). This conclusion is supported by the observation that free-floating car-sharing is used for a much broader variety of trips than station-based car-sharing - an observation also made in other locations (BMW AG et al., 2016; Steer Davies Gleave, 2016). In particular, free-floating car-sharing was indeed found to open up car-sharing for one-way trips, i.e. to the airport or commuting (c.f. Figure B.2),as predicted by earlier research (Ciari et al., 2014; Le Vine et al., 2014) and also observed in other cities (BMW AG et al., 2016; Steer Davies Gleave, 2016; 6t, 2014).

Figure B.5 further shows the systems' impact on their members' overall mode choice behavior. While station-based car-sharing seems to trigger a net shift away from private vehicles and toward public transportation or active modes, the impact of free-floating car-sharing is less clear. In many cases, it reduces use of public transportation or active modes in the favor of car trips. The results are in line with earlier research showing that station-based car-sharing triggers a more efficient use of cars by promoting a gradual shift towards public transportation and active modes (Sioui et al., 2013), as well as first approaches to studying the mode choice impact of one-way and free-floating car-sharing that find a general decrease in public transportation and active mode use among its members (Firnkorn, 2012; Le Vine et al., 2014).

However, this change starts at a high level given that free-floating car-sharing members are particularly frequent users of public transportation (Steer Davies Gleave, 2016). A possible interpretation is that free-floating car-sharing helps to make the whole transportation system more efficient, although quantitative data on the individual travel behavior impact is required to draw sound conclusions.

To better understand the details of car-sharing and use, a sample selection approach was chosen (Table B.4). The model revealed that car-sharing membership is governed by different factors than its use. In particular, university graduates are substantially more likely to become car-sharing members, but do not necessarily use it more. For GA travel card holders, or station-based members (in the case of free-floating car-sharing), the contrast is even stronger – while they are much more likely to become members of a service, they are less likely to actually use it. This result indicates that free-floating car-sharing also works as a complement to public transportation. Even more importantly, the model provides a valuable insight to better interpret earlier research on car-sharing customer groups and to better design future advertising campaigns.

Importantly, this research is one of the first attempts to predict the market size of free-floating car-sharing using empirical data; it revealed that there are probably at least three more Swiss cities with a customer base comparable to Basel.

B.7 CONCLUSION

This research is one of the first approaches to jointly study a free-floating car-sharing and station-based scheme operating in the same city using empirical data. While confirming several aspects already discussed in literature, this research revealed that, due to their different natures, the two schemes address different markets. Moreover, it is also clear that membership and active use of a car-sharing service must be treated separately.

Confirming the expectation that the two car-sharing schemes behave significantly differently from each other makes the question of free-floating car-sharing's environmental impact even more pressing. In contrast to station-based car-sharing, free-floating car-sharing needs not only selected dedicated parking spots, but also access to public space, which usually requires governmental support. And in many cases, official support depends on how well free-floating car-sharing complies with travel demand management and environmental goals. Once, these matters are resolved, the results of this paper indicate that there would be substantial customer bases in many of the larger Swiss cities.

ACKNOWLEDGEMENTS

The survey was commissioned by Mobility Switzerland and involves a parallel Swiss National Fund project (National Research Program 71: Managing Energy Consumption, project number 407140_153807). We would like to thank the two anonymous reviewers for their helpful comments.

C

MEASURING THE CAR OWNERSHIP IMPACT OF FREE-FLOATING CAR-SHARING: A CASE STUDY IN BASEL, SWITZERLAND

This paper has been published as: Becker, H., F. Ciari and K. W. Axhausen (2018) Measuring the car ownership impact of free-floating car-sharing - A case study in Basel, Switzerland, *Transportation Research Part D*, **65**, 51–62

ABSTRACT

Free-floating car-sharing schemes operate without fixed car-sharing stations, ahead reservations or return-trip requirements. Providing fast and convenient motorization, they attract both public transport users and (former) car-owners. Thus, their impact on individual travel behavior depends on the user type. Estimating the travel behavior impact of these systems therefore requires quantitative data. Using a two-wave survey approach (shortly after launch of the scheme plus one year later) including travel diaries, this research indicates that (due to their membership) 6 % of the free-floating car-sharing customers reduce their private vehicle ownership. Moreover, the results suggest that free-floating car-sharing both complements and competes with station-based car-sharing.

CONTRIBUTIONS

The survey was designed by H. Becker and F. Ciari. H. Becker conducted the data collection, developed the concept of the paper and performed the data analysis and interpretation. F. Ciari and K.W. Axhausen supervised the work and provided feedback at various stages.

C.1 INTRODUCTION

Since its first implementation in Ulm, Germany, in 2009, free-floating car-sharing has expanded rapidly around the globe (Shaheen et al., 2015). Instead of relying on fixed car-sharing stations, free-floating car-sharing schemes usually make use of public parking spaces within a designated, citywide service area. Customers can locate and book the closest available vehicle using a smartphone app. At the end of their trip, they can leave the vehicle on any public parking space. Free-floating car-sharing thus offers flexible one-way trips, overcoming key limitations of traditional, station-based car-sharing schemes.

Because free-floating car-sharing schemes require access to public parking spaces, they are more dependent on the support of local authorities. However, concerned about a deteriorating traffic situation, many authorities limit the number of parking permits for free-floating vehicles. Before relaxing such restrictions, they ask for more detailed knowledge about the travel behavior impact of free-floating car-sharing.

Addressing this issue requires new research, because insights from previous studies on station-based car-sharing are in general not transferable to free-floating car-sharing, given their structural differences (Becker et al., 2017a). Moreover, first attempts to determine the net impact on travel behaviour have failed due to a lack of quantitative data (Seattle Department of Transportation, 2014).

This paper reports on an approach, which was designed to allow quantification of the travel behaviour impact of free-floating car-sharing. The method is applied to a new free-floating car-sharing scheme launched in Basel, Switzerland, in August 2014.

C.2 BACKGROUND

C.2.1 *Free-Floating Car-Sharing*

Modern car-sharing dates back to the early 1990s and has seen exponential growth in both customers and fleet size since then (Shaheen and Cohen, 2013). The schemes offer their customers access to cars on an as-needed basis, representing a cheap alternative to a private vehicle - especially for households with relatively low annual mileage (Litman, 2000). Originally, car-sharing operations were exclusively station-based; cars were available at predefined parking spaces (stations) and had to be returned to one of those stations at the end of the trip. While most schemes required the vehicles to be brought back to the start station (round-trip requirement), some of the schemes also permitted one-way trips. Le Vine et al. (2014) suggest that such one-way car-sharing schemes are more attractive to customers, but less of a complement to public transport than round-trip car-sharing.

By lifting the restriction of fixed car-sharing stations as well as allowing one-way trips, free-floating car-sharing is an even more flexible form of car-sharing. First launched in 2009, the number of customers and schemes has skyrocketed in recent years (Shaheen et al., 2015).

C.2.2 *Measuring Car-Sharing Impact*

The environmental and travel behaviour impact of (station-based) car-sharing has been the subject of various studies around the world. Despite different methodological setups, previous studies have consistently found that while a small group of car-sharing members increase their car use, their additional vehicle mileage is more than offset by previous car-owners, who have substantially reduced their car ownership and travel in the course of their car-sharing membership (Martin and Shaheen, 2011a). Moreover, it has been pointed out that the environmental impact exceeds the savings in vehicle miles, because - on average - car-sharing vehicles consume significantly less energy than the private vehicles they replace (Steer Davies Gleave, 2017).

One of the first comprehensive explorations of car-sharing travel behaviour impacts was conducted in Switzerland (Muheim and Reinhardt, 1999). In a survey, respondents were asked to report their travel behaviour both currently and retrospectively, prior to their car-sharing membership. Lacking any travel survey data, the study relied solely on respondents' estimates for their current and past vehicle miles travelled, without any knowledge about the accuracy of such estimates. Moreover, neglecting unobserved heterogeneity, changes in car-ownership and vehicle miles travelled were attributed to car-sharing membership, which probably inflated the actual effect (Mishra et al., 2015). Furthermore, it must be assumed that a retrospective survey approach like this prompts recall bias (Kopec and Esdaile, 1990; Mokhtarian and Cao, 2008), particularly affecting estimates of vehicle miles travelled. Yet, because they impose a low response burden and require minimal administrative effort, similar methodologies have been adopted by many later studies (Martin and Shaheen, 2011a; Lane, 2005; Rydén and Morin, 2005; Martin et al., 2010).

Cervero and Tsai (2004) and Cervero et al. (2007) were the first to address these limitations using a major methodological innovation; in a longitudinal setting, they administered their survey to a panel in multiple waves to overcome recall bias. Moreover, the survey was augmented by a two-day travel diary to strengthen travel behaviour data validity. Finally, a control group was supposed to allow isolation of the actual impact of car-sharing membership from external effects. However, the control group suffered from self-selection issues, probably biasing the results.

Given the later appearance of free-floating car-sharing, there is not yet a great volume of scientific literature dealing with its environmental impact. While early studies predicted a significant reduction in car ownership and CO_2 emissions (Firnkorn and Müller, 2011) from free-floating car-sharing, the actual impact seems to be more complex, as non-car-owners reduce bike, walk and public transit trips, but start to use a (shared) car instead (Firnkorn, 2012).

Some of the early empirical data on the impact of free-floating car-sharing was published by the Seattle Department of Transportation (2014), citing results of a Car2go member survey. The results indicate a rather small reduction in household vehicle holdings. The impact on mode choice remains unclear, given that 40% of the customers claimed to use private cars less often, but 50% of the respondents also stated that they used public transportation less frequently. A related approach conducted in Switzerland yielded similar results (Becker et al., 2017a).

Using a survey approach, as in Muheim and Reinhardt (1999), a recent study by Martin and Shaheen (2016) aimed to define the net impact of free-floating car-sharing. The study indicated a clear trend towards less car ownership and less vehicle miles travelled due to free-floating car-sharing. However, the impacts were calculated based on a non-representative sample. The approach was further enhanced by Le Vine and Polak (forthcoming) and Giesel and Nobis (2016). Again using a retrospective survey approach, they differentiated the impact of free-floating car-sharing on the level of car-ownership by frequency of use, as well as selected socio-demographic variables. However, also in these cases, validity of the resulting car-ownership impacts may be limited due to response bias. An overview of the results of the discussed studies is given in Table C.4. In this research, the net impact of free-floating car-sharing is studied further using quantitative data on individual travel behaviour.

C.2.3 *Survey method*

A common way to collect quantitative data on individual travel behaviour are travel diaries, which capture all activities and trips during a pre-defined survey period. As individual travel behaviour varies over the course of a week, the travel diary should ideally cover multiple days to account for such variation. However, collecting manual (paper-based or CATI[1]) trip diaries was found to yield imprecise and missing data (Bricka and Bhat, 2006; Stopher et al., 2007). GPS-loggers would allow improvement of data quality, but come with high administration cost for the researcher (Montini et al., 2013). The most recent alternative promising to reduce both the response burden and administrative effort while achieving a high data quality is smartphone-based GPS-tracking (Wargelin et al., 2012; Oliveira et al., 2011; Cottrill et al., 2013; Kopp et al., 2015). However, due to smartphone-based systems' novelty, only few surveys have employed them yet. A notable application to research in car-sharing was the German *WiMobil*-study (BMW AG et al., 2016), in which smartphone-based GPS tracking was used to study the travel patterns of car-sharing customers. However, since this was a cross-sectional study, no inferences on the travel behavior impact were possible.

C.3 SETUP

C.3.1 *Methodology*

The methodology used for this research builds on the approach used by Cervero and Tsai (2004). Its limitations are addressed by using a more representative control group and a smartphone-based GPS tracking system to collect travel diaries (i.e. quantitative data on travel behaviour). It uses a panel of

1 computer-assisted telephone interview

two cohorts who were surveyed first shortly after the launch of the free-floating car-sharing scheme and again one year after. Part of each survey wave was a one-week travel diary. One cohort was drawn from members of the free-floating car-sharing scheme, and the second was randomly drawn from the local driver's-licensed population (control group). The general idea of the setup is presented in Figure C.1.

To collect the travel diaries, *Studio Mobilita*[2], a smartphone-based, passive GPS-tracking system has been used. The system uses prompted recall for manual trip mode and purpose imputation by the respondents. In this setup, respondents simply download an app on their smartphone, which automatically tracks their daily trips using the built-in GPS-sensor. Although this allows only smartphone-holders to take part in the study, the validity of the results remains unaffected. As the free-floating car-sharing service can only be used by smartphone-owners, non-owners are excluded from the service by design.

The chosen setting allows a before-and-after comparison of travel behaviour. Moreover, the representative control group allows isolation of the actual free-floating car-sharing impact. Since no pre-registration in the free-floating car-sharing scheme was available, it was impossible to identify members before the launch of the scheme. Therefore, the first stage of the survey was carried out 6 weeks after the launch of the scheme.[3] However, it is assumed that, in this short time frame, no substantial changes in travel behaviour took place. This assumption is supported by previous research indicating that the main effects of a car-sharing service occur within the first two years of its operation (Cervero et al., 2007).

C.3.2 *Context*

The study was conducted in Basel, the third-largest city in Switzerland (approx. 160 000 inhabitants). Basel is situated in the north-western part of the country and shares borders with both France and Germany. Divided by the river Rhine, its actual city centre is located in the southwest half of the city, although there is also substantial cultural and economic activity in the northeast parts of the city. Basel has a net influx of commuters, with an

2 www.studio-mobilita.ch
3 In most cases, the actual time between registration with the service and the survey was lower, because during the first months, uptake of the scheme increased over time.

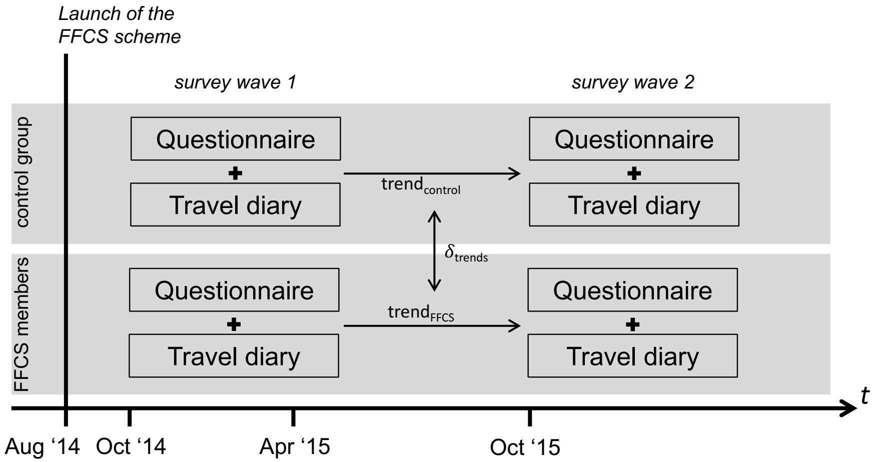


FIGURE C.1: Study design

average of 1.4 work places per inhabitant. With a car mode-share of 18% of all trips, it is the least car-oriented of the larger Swiss cities. In turn, it has relatively high mode shares for public transportation (27%) and bike (16%). Following this pattern, Basel also has the lowest degree of motorisation of the larger Swiss cities (352 registered cars per 1 000 inhabitants). The low motorisation is powered by a dense network of public transportation including rail, metro, tramways and buses. Still, the city has an estimated total of 100 000 parking spaces (both private and public). While public on-street parking was free of charge for the public at the beginning of this study, the city of Basel has gradually moved towards either pricing on-street parking or making it exclusive for residents of the respective neighbourhoods. For more detailed information on the transport system in the city of Basel, the interested reader may refer to Planungsbüro Jud (2012).

A free-floating car-sharing scheme was launched in Basel in late August 2014. Starting with 100 vehicles in the inner city of Basel as its operating area, it has since expanded to cover the whole canton of Basel-Stadt, as well as a small number of neighbouring municipalities. Meanwhile, the fleet size was increased to 120 vehicles. The system is open to anyone holding a driver's license. There is a 15 CHF registration fee, but no annual membership fees. Rentals are charged by the minute.

C.4 DATA COLLECTION

C.4.1 *Recruitment*

In total, 1 218 free-floating members and 6 000 members of the random sample were invited to take part in the study. Address lists of car-sharing members were made available by the operator; surface mail addresses for the random sample of the Canton Basel-Stadt population above legal age were provided by the Cantonal Statistical Office of Basel-Stadt.

Each survey wave consisted of two parts. The first was a questionnaire about socio-demographic attributes, attitudes and mobility behaviour; the second part was a week-long travel diary using the system *Studio Mobilita*. Respondents were asked to complete the questionnaire by the end of the week of receipt and to keep the diary the week after. Details and instructions concerning the travel diary were given on completion of the questionnaire.

While car-sharing members were recruited via e-mail and were able to access the web-based survey using personalized web-links, members of the control group received the survey in pencil-and-paper format via surface mail, including a reply-paid envelope. For company policy reasons, it was not possible to contact car-sharing members via surface mail. However, for the control group, no e-mail addresses were available. This asymmetric setting may have given rise to selection bias, which was addressed by applying sample weights to the responses, as detailed later in this section.

Moreover, car-sharing members were initially only to be invited to the questionnaire. On completion of the questionnaire, respondents were automatically invited to take part in the travel diary and were promised a 20 CHF (equivalent to 13 USD at purchasing power parity) credit on their next car-sharing bill. In contrast, members of the control group received all the necessary information along with the questionnaire. As incentive, they were offered 20 CHF in cash in return for their full participation.

Survey invitations for the first wave were administered to the respondents in weekly cycles between October and December 2014. Hence, the survey started about six weeks after the launch of the scheme in late August 2014. Invitations for the second wave were administered one year later, i.e. between October and December 2015. In the last week of each survey wave, reminders were sent out to all those car-sharing members who had failed to complete the survey by then. Respondents overdue in completing their mobility diary, were offered assistance. Moreover, given the relatively small initial growth rates in membership, free-floating car-sharing members having joined the service between January and March 2015 were invited to take the survey in early April 2015. They were treated as part of the first wave. In order to allow enough time to the second survey wave, respondents to the April-wave were invited to the second survey wave in November 2015[4]. Overall, half of the respondents from the free-floating car-sharing group were recruited at this later stage. Yet, given that the distribution of age, gender and income of this later group was not significantly different from the earlier wave in fall 2014 and that the weather was also comparable, the responses were pooled and treated as part of the first survey wave in late 2014.

C.4.2 *Data acquisition*

First-wave respondents needed an average of 18 minutes and second-wave respondents 15 minutes to complete the web-based survey. With this rather short survey time, fatigue effects causing response bias and reducing the likelihood of proceeding to the travel diary were minimized.

The response rates for the different survey waves are summarized in Table C.1. In the first wave, 366 free-floating car-sharing members returned a complete questionnaire and 91 completed the travel diary. From the control group, 594 questionnaires and 226 travel diaries were collected. Only respondents, who completed the questionnaire in the first wave were invited to the second wave. The *valid diaries* consist of users who provided comparable diaries for both waves (see section 4.2 for details).

Compared to previous surveys (Axhausen et al., 2015b), response rates shown in Table C.1 were well within the expected range. The slightly higher response rate among free-floating car-sharers may be explained by the fact that they were contacted on behalf of a service they had recently joined and could therefore be regarded as pre-recruited.

4 The shorter time between the two waves for this part of the sample may result in a certain underestimation of the actual car-sharing impact.

	first wave		second wave	
	free-floating	control	free-floating	control
Invitations sent	1 218	6 000	366	594
Surveys completed	366	594	224	284
with drivers license	366	447	224[a]	209[a]
Response rate of the eligible	30%	10%	61%	48%
Diaries completed	91[b]	226	52[b]	88
Response rate of the eligible	25%	51%	23%	42%
Valid diaries			37[c]	35[c]
Legs in valid diaries			2 743	2 332

a: sample used for estimation of impact on car-ownership.

b: sample used for analysis of use cases.

c: sample available for estimation of impact on mode share.

TABLE C.1: Response rates per response group

In contrast, the response rate achieved for the diaries was much lower than expected. From earlier experiences, it was expected that around 80% of the respondents would proceed to the travel diary after having completed the questionnaire. However, the response rate turned out to be substantially lower. Based on respondents' feedback and the fact that almost all dropouts occurred when respondents had to confirm a data privacy declaration, the authors assume that this drop in response rate could be attributed, at least partly, to data privacy concerns.

Data collection was partly shared with Becker et al. (2017a), who use the 2015 cross-section of the questionnaires (sample extended with additional (new) respondents) to analyze user groups and usage patterns of free-floating and station-based car-sharing. The paper also presents a detailed analysis of the socio-demographic variables of the response groups.

C.4.3 *Data preparation*

Only completed questionnaires were considered for the analysis. Moreover, responses from car-sharing members who completed the survey in less than seven minutes (a third of the average time) were excluded. Finally, unreasonable answers were identified on a per-question basis (e.g. year of birth before 1900). Members of the control group not holding driver's licenses were excluded from the analysis, under the assumption that they were not within the car-sharing target group.

To correct for gender and age selection bias, statistical weights were applied to individual responses. The respective marginal distributions were obtained from address lists provided by the operator for members and from a national travel survey (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012) for the control group. Spatial distribution of homes was also studied. However, since only random deviations were found, spatial effects were omitted, given the excellent access to public transportation throughout the study area.

Records from the travel diaries were also carefully prepared for the analysis. In a first step, all responses recording less than three full days per survey period were dropped and only the remaining diaries were regarded as complete. In a second step, respondents who completed the prompted recall for less than 75% of their trips were excluded. All remaining travel diaries were then carefully reviewed manually to ensure validity of the records and comparability of the two survey periods (e.g. to exclude holiday period effects). As shown in Table C.1, relatively few valid diaries were left after this process. Still, for the control group, the key variables (number of trips, daily distance, mode share) matched the results of the national travel survey (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012) for Basel. Therefore, the observations can be assumed valid and provide a deep insight into changes in individual travel behavior possibly induced by free-floating car-sharing.

C.5 DATA ANALYSIS

The setup would allow to study three key aspects of the travel behaviour impact of free-floating car-sharing: the impact on the level of car-ownership, on mode choice and on vehicle miles travelled. However, given the unexpectedly low turnout of valid travel diaries, the quantitative analysis on vehicle miles traveled had to be dropped.[5] Of the remaining two analyses, the first part is a quantitative panel-analysis of the survey data, while the second part provides qualitative insights into the travel diaries.

5 Given the large inter- and intra-person variability in travel behaviour, it cannot be assumed that such a small group was representative for the respective population.

To determine the impact on car ownership, several approaches are introduced to account for existing intentions to buy or sell vehicles. The impacts of free-floating car-sharing are then calculated using difference-in-differences approaches, as well as a population-averaged Poisson and negative-binomial model. Whilst a simple difference-in-difference method has already been employed by Cervero and Tsai (2004), a population-averaged Poisson or negative-binomial modeling approach is a widely used tool in count panel data analyses (Cameron and Trivedi, 2015). Both approaches allow to control for exogenous variables, such as income or subscriptions for public transportation. For this analysis, only respondents with a drivers license, who did not report a change in their employment status, work location or home location between the two survey waves were considered, yielding a remaining 204 control group observations and 191 free-floating car-sharing members.

The impact on mode use was studied using a qualitative analysis of the travel diaries. To this end, activity chains involving use of free-floating car-sharing were compared to similar activity chains from the same respondent, where free-floating car-sharing was not used. To the authors' best knowledge, no similar approach has been used by any previous car-sharing study. It provides new valuable insights into use of free-floating car-sharing.

C.5.1 *Car Ownership Impact*

In a first step, data from the surveys was used to estimate the impact of the free-floating car-sharing scheme on car ownership levels. To this end, different ways of framing the impact on car-ownership were introduced and analysed.

It was established that, from the beginning, free-floating car-sharing members owned substantially fewer cars than the control group (0.27 vs. 0.84 vehicles per household in first survey wave) and this difference is significant ($t = -10.7$). Within the first year of operation of the free-floating car-sharing scheme, both groups slightly decreased their levels of car ownership to 0.24 and 0.83 vehicles per household, although those reductions are not statistically significant.

The impact of free-floating car-sharing on household vehicle holdings can be assessed in two different ways. Either the actual level of car ownership in the second year can be compared to the level of car-ownership respondents reported in first-year survey or it can be compared to the level of car ownership, respondents had anticipated for the second year when asked in the first-year survey. In the following, the two references will be denoted as actual number of cars and anticipated number of cars. The actual number of cars represents the number of cars reported in the first survey wave. The anticipated number of cars is based on this actual number of cars to which one car was added or subtracted in case the respondent stated plans to buy or sell a car within twelve months from the first survey wave.

Introducing the anticipated number of vehicles as possible reference was motivated by the observation that 3% of the free-floating car-sharing members stated that they had planned to buy an additional car. Anticipated car ownership averaged at 0.29 vehicles per free-floating car-sharing household and at 0.80 vehicles per control group household. It is noteworthy that the control group intended to decrease their level of car ownership. This effect may be due to the introduction of parking fees for on-street parking throughout Basel city, which has been introduced in multiple steps between 2014 and 2016. However, again, within-group differences between anticipated and second-wave car-ownership levels are not significant.

Using a difference-in-differences approach, change in car ownership levels of the free-floating car-sharing households can be compared to the control group. While no significant effect was found comparing the second-wave level to the actual first-wave level of car ownership, using the anticipated level of car ownership yields a significant difference in differences ($t = -2.34$). In this case, free-floating car-sharing members have decreased their level of car ownership compared to the control group by 0.07 vehicles per household.

However, a simple comparison of the group means does not necessarily reveal the true impact of a free-floating car-sharing membership, because the observed changes may also be due to fluctuations in other, e.g. sociodemographic characteristics. To correct for such influences, three covariates expected to have an impact on vehicle ownership were considered (van Eggermond et al., 2016). As shown in Table C.2, when controlling for household income, GA travel card ownership (a subscription allowing un-

Reference	actual car ownership		anticipated car ownership	
	Coeff.	t	Coeff.	t
Household income [kCHF]	0.028***	4.55	0.027***	4.45
GA travelcard	-0.195***	-3.58	-0.208***	-3.82
City center home	-0.134***	-2.57	-0.133**	-2.53
Baseline diff.	-0.535***	-9.35	-0.479***	-8.24
Follow-up diff.	-0.614***	-11.41	-0.611***	-11.33
Diff.-in-Diff.	-0.079*	-1.89	-0.132***	-3.06
	$N = 790$		$N = 790$	
	$R^2 = 0.27$		$R^2 = 0.26$	
*Significance codes: 0.10 * 0.05 ** 0.01 ****				

Table C.2: Difference-in-Differences Approach for Car Ownership

limited use of public transportation across Switzerland) and home location (city centre vs. agglomeration), the difference in differences is significant for both reference cases: Free-floating car-sharing members reduced their level of car ownership by 0.08 cars compared to their actual earlier level (significant at the 10% level) and by a significant 0.13 cars compared to their anticipated level (significant at the 1% level).

Both models presented in Table C.2 consistently indicate that free-floating car-sharing members reduce their level of car ownership compared to the control group. Yet the first model ignores initial intentions about a change in ownership level, while the second model assumes that there are no deviations from those initially stated intentions. To overcome the two models' limitations, a simple population-averaged poisson model for the actual level of car ownership was estimated. The model equation is

$$\ln E(y_{it}) = \alpha + \delta_{t,1}\gamma + \mathbf{x}_{\mathbf{it}}^{\mathbf{T}}\boldsymbol{\beta}, \qquad y \sim \text{Poisson},$$

where y_{it} is the number of cars in the household of individual i at time $t \in \{0, 1\}$. α denotes the (time-invariant) constant and $\delta_{t,1}$ is a dummy variable indicating observations from the second survey wave. x_{it} are the exogenous explanatory variables. Estimation is done using Generalized Estimating Equations (Liang and Zeger, 1986). The Poisson model was assumed appropriate, because the relative difference between $\mu_y = 0.53$ and $\sigma_y^2 = 0.65$ was small. However, a regression-based test by Cameron and Trivedi Cameron and Trivedi (1990) indicated significant overdispersion in the data ($t = -8.05$). Therefore, the model was re-estimated as a population-averaged negative binomial model.

	Poisson		neg. binomial	
	Coeff.	z	Coeff.	z
# of cars in household				
University degree	-0.235*	-1.94	-0.256**	-2.08
Household income [kCHF]	0.029**	2.48	0.028**	2.34
Household size	0.076*	1.71	0.080*	1.75
Home at transit level A	-0.400***	-3.30	-0.399***	-3.27
Free-floating member	-0.234***	-4.13	-0.282***	-4.49
Free-floating member # car intentions	0.688***	3.37	0.816***	4.37
Time dummy	0.071*	1.79	0.080*	1.86
Constant	-0.791***	-4.18	-0.784***	-4.08
	$N = 790$		$N = 790$	
	Wald$\chi^2(7) = 66.29$***		Wald$\chi^2(7) = 76.71$***	
	pseudo $R^2 = 0.11$		pseudo $R^2 = 0.12$	

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

pseudo R^2 calculated as the square of the correlation between predicted and actual values

TABLE C.3: Population-Averaged Model for Car Ownership

To improve efficiency, some covariates from the difference-in-differences models were dropped and replaced by new variables. This population-averaged model can be interpreted as explaining the average effect of free-floating car-sharing membership on its members' car-ownership level. The model is assumed to be the most suitable of the approaches presented in this section. The results are presented in Table C.3. Indeed, parameter estimates for the negative binomial model are slightly different from the Poisson model, although differences are not substantial. In the following, interpretations are based on the negative binomial model. As presented in Table C.3, the model indicates that university graduates and people living in areas well served by public transportation own fewer private cars[6].

6 Transit service levels as defined in the Swiss standard SN 640 290. Level A is the highest level of transit connectivity and requires a departure interval of, at most, 5 min per main load direction at rail stops in a 500m perimeter

In turn, car ownership increases with household income.[7] These results are in line with earlier research on mobility tool ownership in Switzerland (Becker et al., 2017c). The effect of free-floating car-sharing membership was then estimated separately for those respondents who claimed that they intended to buy an additional car and for those who planned no change in their car ownership. Members not planning to buy a car decreased their level of car ownership by about 24 %[8]; members planning to buy a car substantially expanded their fleet. Thus, free-floating car-sharing generally reduces car ownership, except among members who had already planned to expand their fleet when they joined.

C.5.2 *Free-floating Use Cases*

The second step consisted of a qualitative analysis of completed travel diaries to learn more about how free-floating car-sharing is used. To this end, all recorded days containing at least one free-floating car-sharing ride were identified. For each of those observations, a second recorded day with a similar activity chain, but without car-sharing use, was searched to allow a pairwise comparison[9].

In total, 60 recorded days containing 96 free-floating car-sharing rides were available for the analysis. A corresponding trip without car-sharing use could be found on another day for only 17 of the 60 recorded days with car-sharing use. These trips mostly involved complex trip chains consisting of many (different) activities at multiple locations. This suggests that the scheme is mainly used for non-regular activity patterns, i.e. for activity patterns not occurring with frequent (at most weekly) repetition. In fact, 17% of all recorded free-floating car-sharing trips were leisure trips and 7% were escort trips. Shopping and errands covered another 11% of the trips. Recurring trip purposes, such as work or education, were served by only 13% of the trips. 40% of the trips had their destination home. 21% of the trips occurred at night between 10pm and 6am. Moreover, 25% of the trips started or ended outside the service area, meaning that they were part of a tour including at least one more (return) free-floating trip. In fact, during

7 Although university degree and income are correlated in this sample ($\rho = 0.26$), this correlation does not substantially affect the parameter estimate of free-floating car-sharing membership.

8 Calculated as $e^{\beta_{\text{FFCS member}}} - 1$.

9 For this purpose, all records of each respondent were compared manually. The main criterion was a similar sequence of activities.

half of the recorded days, free-floating car-sharing was used for more than one trip.

From the 17 car-sharing uses with a corresponding record, two typical use cases stand out. They are presented in Figure C.2.

- User type A (4 observations) is a long-haul commuter. They use free-floating car-sharing on their commute to or from the train station, when they have to catch an early train or arrives home late. In the example presented in Figure C.2, the train runs 40 minutes earlier than usual, which would involve an unfavourable tram connection on the first mile to the train station. 15% of the recorded trips either started or ended at the central train station.
- User type B (4 observations) is an occasional car user replacing his car use by both public transportation and free-floating car-sharing. In the example presented in Figure C.2, he usually commutes to work by bike. When he had to go shopping on the way home, he usually took the car to work and shopped on the way home. After the launch of the free-floating car-sharing scheme, he continues to commute by bike. But on his shopping days, he takes public transportation to work and uses free-floating car-sharing to do the shopping on his way home.

The low number of observations permits only qualitative analysis. In particular, shares of trip purposes or times of day cannot be assumed to be representative for overall scheme use. Nevertheless, the data provides three interesting insights: first, free-floating car-sharing is mostly used for non-regular trip patterns. Second, if used in a regular trip pattern, it replaces both car and public transport trips, with the latter replaced mostly for early morning, late evening or longer intra-urban trips. Third, none of the free-floating car-sharing members was found to directly substitute active modes or public transport by free-floating car-sharing without any further alterations in the trip chain.

C.6 DISCUSSION

Most of earlier research to determine the travel behavior impact of car-sharing has been conducted using retrospective surveys, which directly ask respondents about their current and past behavior as well as the degree to which car-sharing was the reason for potential changes (Martin

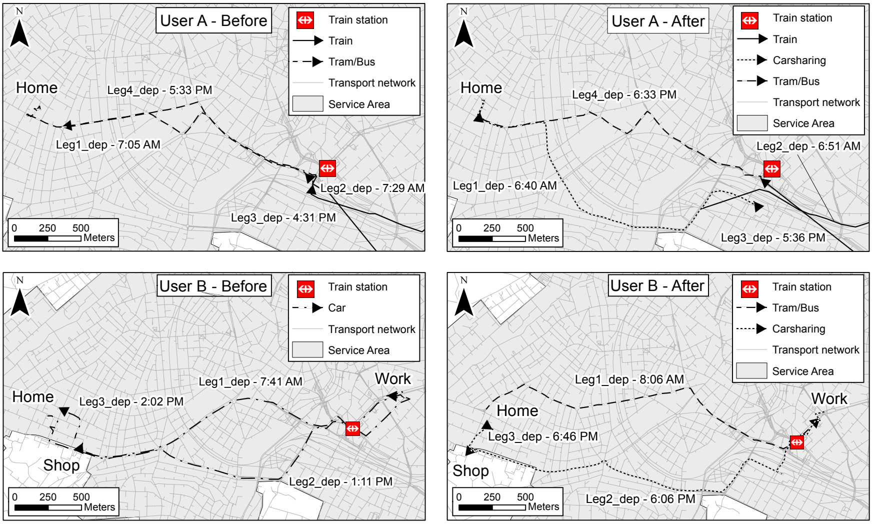


FIGURE C.2: Car-Sharing Use for Regular Activities

et al., 2010). This strategy acknowledges that there are many (and often unknown) factors involved in travel behavior decisions and assumes that the respondents themselves are the most qualified to judge the impact their car-sharing membership had on their choices. Although this approach has its merits, it is also prone to recall bias, attribution bias, strategic responses and other limitations. This research aims to address such response biases by using a before-and-after comparison with quantitative travel behaviour data of both members and a control group. In this research, unobserved heterogeneity can be controlled for through a control group, whereas recall bias is eliminated through the two-wave approach, in which only information on present behavior is asked.[10]

Using this new appraoch, this research provides further insights into the travel behaviour impact of free-floa-ting car-sharing, showing that free-floating car-sharing members reduce their level of car-ownership. Model results indicate that free-floating car-sharing reduces the ex-ante car-ownership level of 0.27 vehicles per household by 24%. This effect corresponds to a reduction of 0.06 vehicles per household or 6 % of the member house-

10 Given that the first survey wave took place a few weeks after respondents had joined the free-floating car-sharing scheme, the resulting effects may be slightly underestimated. However, this bias is assumed to be small since car ownership decisions are usually not taken that fast.

holds reducing their level of car-ownership. The results are in line with earlier research (Le Vine et al., 2014) suggesting that impacts of free-floating car-sharing are weaker than those of station-based car-sharing.

Notably, these model results also indicate a substantially lower impact than indicated in the survey, where 8% of free-floating car-sharing members stated that they would buy an (additional) car if free-floating car-sharing was not available Becker et al. (2017a). The car ownership impact in the model results is also lower than the observed change in vehicle holdings of 0.08 vehicles per household. This implies that the observed change in vehicle ownership cannot be entirely attributed to car-sharing membership. In addition, the analysis shows that using the intended level of car-ownership would lead to even more inflated results (reduction of 0.13 vehicles per household).

The model results are in line with results by Martin and Shaheen (2016), who reported a 5% reduction in household vehicle ownership for car2Go customers in Washington, DC. Although car-ownership impact of free-floating car-sharing is substantial, it is substantially lower than both early predictions for free-floating car-sharing by Firnkorn and Müller (Firnkorn and Müller, 2011) and the widely accepted impact of station-based car-sharing, where 15-20% of all joining households are thought to have given up private car ownership (Muheim and Reinhardt, 1999), based on a (probably biased) stated-reduction approach.

Results from qualitative analysis of free-floating car-sharing use cases show that the scheme is mainly used for non-regular activities. In particular, a substantial share of free-floating trips are actually multi-stage or return trips, which indicates that free-floating car-sharing is also used for trip patterns that would have been an original motivation for station-based car-sharing.

In the rare cases when free-floating car-sharing is used within a regular travel pattern, it does not directly substitute for public transport or active modes, except for connection with an earlier or later departure time, or other alterations to the routine. Yet, it allows some of its members to replace a car-only routine by both public transport and car-sharing. Thus, the observations from travel diaries support the theory that free-floating car-sharing does not necessarily lead to more car traffic. Also, these findings complement earlier research showing that free-floating car-sharing is used most often in situations, for which public transport is not attractive Becker et al. (2017b). Further, a substantial share of the free-floating car-sharing trips are multi-stage or round trips. Hence, it can be assumed that at least for shorter trips into the immediate surroundings of the city, the free-floating car-sharing scheme not only complements, but partially competes with existing station-based car-sharing schemes.

Although this research can determine the car-ownership impact of free-floating car-sharing, significant results about mode choice and environmental impact could not be obtained because of the small sample size. Given the substantial variation in individual travel behaviour, a sample size of about 300 valid travel diaries would have been required to more significantly determine the effect of free-floating car-sharing on car use and fuel consumption.

C.7 CONCLUSION

Station-based car-sharing enables its members to shift from a car-oriented to a public transport-oriented lifestyle by providing a car on an as-needed basis (Shaheen and Cohen, 2013). Given that free-floating car-sharing, due to its flexibility, is less predictable and therefore less reliable than station-based car-sharing from a customer's point of view, the question was; does it have a similar leverage effect on travel behaviour to station-based car-sharing? This research presents one of the first attempts to use quantitative, empirical data to address this question. It begins to confirm that free-floating car-sharing substantially and significantly reduces the level of car-ownership and triggers a modal shift towards public transportation.

In contrast, impacts on vehicle miles travelled and energy consumption could not be precisely determined due to the low number of valid travel diaries. Yet, when seen in light of the significant and substantial reduction in the level of car-ownership and the observation that none of the free-floating car-sharing members directly substituted active modes or public transportation with free-floating car-sharing, the results suggest that there is no net increase in car travel caused by free-floating car-sharing. Further research is also needed to quantify the impact on vehicle miles traveled and to better understand the causal nature of the reductions in car-ownership and (potentially) use.

However, already at this stage, the results provide policy-makers with a better understanding of free-floating car-sharing impacts. It was confirmed that - despite a slightly weaker impact than for station-based car-sharing - free-floating car-sharing also triggers a shift away from private vehicle ownership. Instead, it seems to complement a public-transportation oriented lifestyle. Given these positive impacts on the transportation system, some cities may find it easier to allow free-floating car-sharing operators access to the on-street parking places they need for their operations.

With respect to methodology, results suggest that the actual impact of a car-sharing scheme may be weaker than changes in car ownership or travel behaviour stated by its members in a retrospective survey. The difference is significant and stresses the importance of not solely relying on survey results for valid impact estimation.

ACKNOWLEDGEMENTS

The study was commissioned by Mobility Switzerland and involved a parallel Swiss National Fund project (National Research Program 71: Managing Energy Consumption, project number 407140_153807). The authors thank the three anonymous reviewers for their valuable feedback.

C.8 IMPACT OF CAR-SHARING MEMBERSHIP ON PRIVATE VEHICLE HOLDINGS

The following table provides an overview of selected studies estimating the impact of car-sharing schemes on their members' private vehicle holdings. The results were usually reported in three key numbers:

- *reduction in car-ownership*: What share of car-sharing members have reduced their private vehicle holdings due to their membership in the car-sharing scheme?
- *foregone purchase of private car*: Typically, members are asked, whether they would buy a private vehicle, if the car-sharing scheme was unavailable (or would suddenly disappear).
- *replacement rate*: How many private vehicles are replaced per car-sharing vehicle?

So far, there has not been a common procedure to estimate these numbers. While in some cases, the reported impact was weighted by the relative importance of car-sharing (Martin et al., 2010) or to account for intention-behavior gaps (Firnkorn and Müller, 2011), in other cases, the plain responses were presented. Moreover, the two first numbers are sometimes added to obtain the combined impact on vehicle holdings. However, one would have to expect that this would result in double-counting of members, who have shed a car due to their car-sharing membership (and who would therefore likely buy a car in the absence of the scheme).

year	location	data origin	car-sharing type	reduction in car-ownership	foregone purchase of private car	replacement rate	source
1998	Switzerland	cross-sect., CATI	station-based	15-20 %	20-25 %	1 : 2.5	Muheim and Reinhardt (1999)
2001	San Francisco, CA	panel, paper surv. & tracking	station-based	21 %	28 %	1 : 7	Cervero and Tsai (2004)
2003	Philadelphia, PA	cross-sect., online surv.	station-based	25 %	29 %	1 : 23	Lane (2005)
2008	United States & Canada	cross-sect., online surv.	station-based	22 %[(a)]	25 %	1 : 9-13	Martin et al. (2010)
2011	Ithaca, NY	cross-sect., online surv.	campus	-	18 %[(a)]	1 : 15	Stasko et al. (2013)
2015	Berlin & Munich, Germany	cross-sect., online surv.	station-based	15 %	-	-	Giesel and Nobis (2016)
2016	London, United Kingdom	cross-sect., online surv.	station-based	16 %	34 %	1: 11	Steer Davies Gleave (2017)
2009	Ulm, Germany	hypothetical, intercept surv.	free-floating	4 %	10 %	-	Firnkorn and Müller (2011)
2015	United States & Canada	cross-sect., online surv.	free-floating	2-5 %	7-10 %	1 : 8-11	Martin and Shaheen (2016)
2015	Berlin & Munich, Germany	cross-sect., online surv.	free-floating	7 %	-	-	Giesel and Nobis (2016)
2015	London, United Kingdom	cross-sect., online surv.	free-floating	4 %	30 %	-	Le Vine and Polak (forthcoming)
2015	Basel, Switzerland	cross-sect., online surv.	free-floating	-	8 %	-	Becker et al. (2017a)
2016	London, United Kingdom	cross-sect., online surv.	free-floating	19 %	27 %	1: 11	Steer Davies Gleave (2017)
2015	Basel, Switzerland	panel, online surv. & tracking	free-floating	6 %	-	-	*(this paper)*

[a] own calculation based on numbers in the respective paper.

Table C.4: Earlier research on car-sharing impact on members' vehicle holdings (selection).

D

MODELLING FREE-FLOATING CAR-SHARING USE IN SWITZERLAND: A SPATIAL REGRESSION AND CONDITIONAL LOGIT APPROACH

This paper has been published as: Becker, H., F. Ciari and K. W. Axhausen (2017b) Modelling free-floating car-sharing use in Switzerland: A spatial regression and conditional logit approach, *Transportation Research Part C*, **81**, 286–299

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.

CONTRIBUTIONS

The study was designed by H. Becker and K.W. Axhausen. H. Becker pre-processed the data and performed the data analysis and interpretation. F. Ciari and K.W. Axhausen supervised the work and provided feedback at various stages.

D.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 (Shaheen et al., 2015). 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 (BBC, 2014; Smiley, 2016). It appears that even after several years on the market, only little is known about which factors govern free-floating car-sharing demand (Kortum et al., 2016).

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 available for the car-sharing scheme correspond to about 82% of the total number of on-street parking spaces in the city.

D.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 (Litman, 2000). It was also found, that younger, highly educated and car-free households are most likely to become car-sharing members (Burkhardt and Millard-Ball, 2006; Becker et al., 2017c). Moreover, there is agreement that car-sharing facilitates a car-free lifestyle by providing a vehicle in situations, in which it is actually needed (Shaheen and Cohen, 2013). This way, it helps to reduce car-ownership and vehicle miles travelled (Martin et al., 2010; Martin and Shaheen, 2011a).

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 (2007) 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. (2009) 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. (2016) 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 (2013) 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. (2013) 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.

A step towards opening car-sharing up to new markets was the introduction of station-based one-way car-sharing, where the return-trip requirement is relaxed and customers may end their trip at any car-sharing station. However, for such schemes, imbalances in the spatio-temporal demand distribution require substantial efforts of vehicle relocations or user incentives (Jorge et al., 2015b). As an alternative, the one-way option can be reduced to trips between selected station and a point of interest with high demand (Jorge et al., 2015a).

An even more flexible form is free-floating car-sharing. It operates without fixed car-sharing stations and return trip requirements. Due to such structural differences to station-based return-trip services, it was found to attract different customer groups and to also have a different impact on travel behavior (Le Vine et al., 2014; Becker et al., 2017a; Le Vine and Polak, forthcoming). Therefore, knowledge about the drivers of station-based car-sharing demand as outlined above may not be applicable to free-floating car-sharing.

This notion is supported by early agent-based simulations showing substantial differences in the demand patterns of the two systems (Ciari et al., 2014). In addition, agent-based simulations were further used to study e.g. the effect of different pricing schemes and parking prices on free-floating car-sharing demand (Ciari et al., 2015a; Balac et al., 2017). However, so far, the results of these and other agent-based approaches to model car-sharing (Heilig et al., 2017) are limited by the lack of dedicated mode choice models covering any form of car-sharing.

In a first approach to better understand free-floating car-sharing adoption using empirical data, Kortum and Machemehl (2012) 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. (2015) 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 and Machemehl (2012) and Schmöller et al. (2015) 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.

D.3 DATA

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

D.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

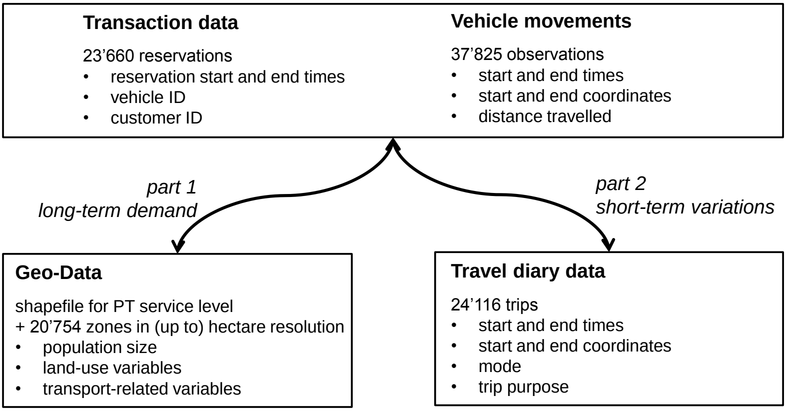


Figure D.1: Data sets used in this research

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.

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 minutes 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 ad-

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

dresses were geo-coded using the GoogleMaps GeoCoding API (Google, 2016). 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.

D.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 (Bau- und Verkehrsdepartement des Kantons Basel-Stadt, 2016). 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.

D.3.3 *Travel diary data*

Electronic travel diary data of free-floating car-sharing members were available from a related study in the area (Becker et al., 2018). 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

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.

data set includes an only insignificant number of trips conducted by free-floating car-sharing.

D.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.

D.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 (Becker et al., 2017a). 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 (Hansen, 1959). Thus a rough estimate of accessibility was calculated and added to the data set. The calculation followed the original formulation suggested by Hansen (1959):

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

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 sec-

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

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

ond case represents the number of workplaces in the given zone. Although more advanced formulations of accessibility are available (Axhausen et al., 2015a), 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` (Chambers, 1992) and `spreg` (Piras, 2010).

D.4.2 *Results*

Figure D.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 (Anselin et al., 1996) indicates significant spatial dependence for both the dependent variable and the disturbances ($\mathrm{LM}_{err} = 163.42$, df$= 1$, $p < 2.2 \cdot 10^{-16}$; $\mathrm{LM}_{lag} = 194.91$, df$= 1$, $p < 2.2 \cdot 10^{-16}$), a linear Cliff-and-Ord-type (Cliff and Ord, 1973) 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.

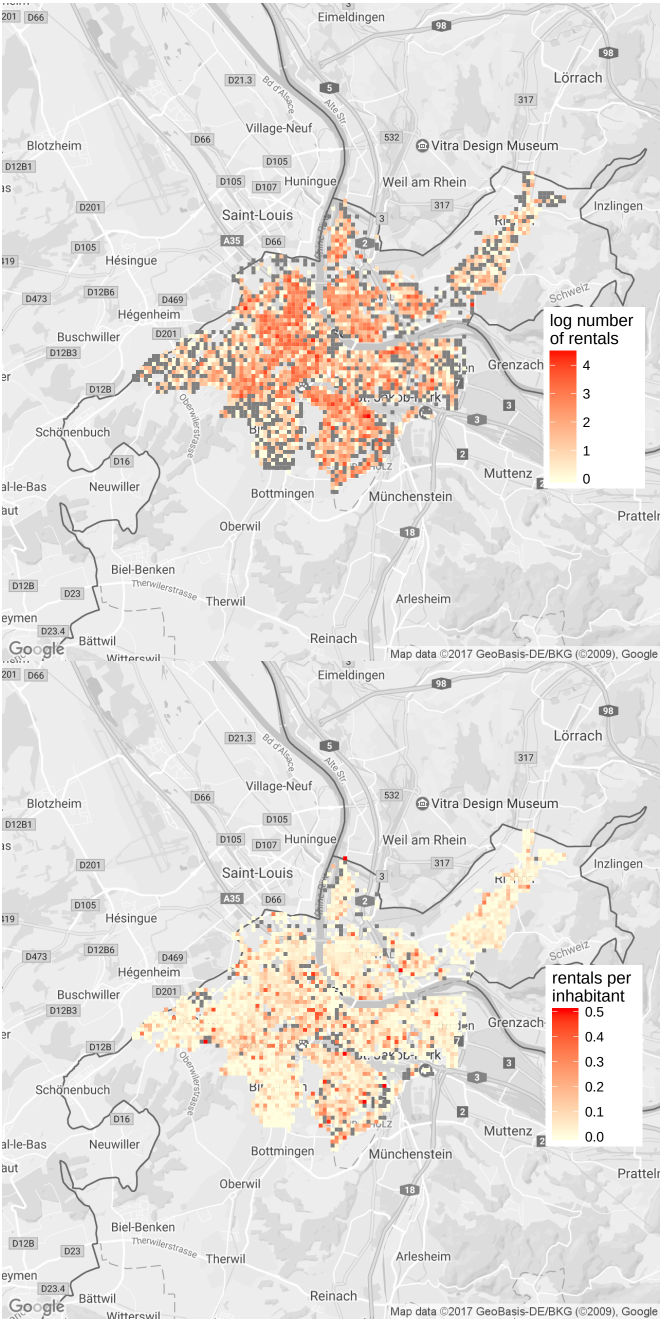


FIGURE D.2: Free-floating car-sharing rentals per hectare

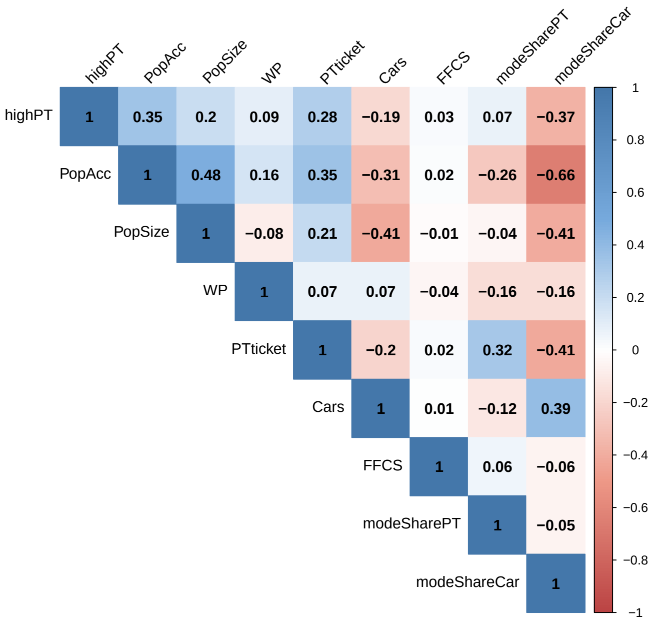


Figure D.3: Correlation matrix of spatial attributes

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 (Kelejan and Prucha, 1999). Therefore, the model was estimated using a general method of moments approach. Table D.1 summarizes the attributes used in the final model, Figure D.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 D.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 D.2 - a substantial share of the variance can be explained by the population size of an area. Also the

	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 ***			

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

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.

D.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.

D.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 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 (Swait and Ben Akiva, 1987). 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 (Becker et al., 2017a). 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

3 In addition, 73.2% of the free-floating car-sharing members do not even have a private car in their household (Becker et al., 2017a).

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%

TABLE D.3: Choice frequencies

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 multinomial logit model. To do so, each of the trips was routed using the GoogleMaps Directions API (Google, 2016) 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 D.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 table for public transportation in Switzerland [4]. 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 (Becker et al., 2017a), 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.[5]

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 conditional logit model (McFadden, 1974b). For each case[6] $i = 1, ..., N$ and alternative $j \in \{\text{walk}, \text{bike}, \text{car-sharing}, \text{public transportation}\}$, the utility function of this model can be expressed as

$$u_{ij} = v_{ij} + \epsilon_{ij} = \mathbf{x}'_{ij}\boldsymbol{\beta} + \mathbf{z}'_i\gamma_j + \epsilon_{ij}$$

where $\mathbf{x}_{ij}$ is a $r \times 1$ vector of alternative-specific regressors (with r being the number of alternative-specific regressors) and $\mathbf{z}_i$ is a $q \times 1$ vector of case-specific regressors (with q being the number of case-specific regressors). γ_{walk} is set to zero to represent the base category. ϵ_{ij} are assumed

4 T600 - Allgemeiner Personentarif `http://voev.ch/T600`

5 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).

6 Here, a case is defined as a choice situation. Given that the choice situations are individual-specific, there is no differentiation between the decision-makers at this point.

extreme value type I distributed random variables (Gumbel, 1960). Yet, the observations have to be assumed conditionally correlated due to the fact that the data contains multiple observations per respondent. Hence, a cluster-robust estimator of the variance-covariance matrix of the estimators is used in this case (Cameron and Trivedi, 2009).[7] The choice probability for case i and alternative j reads

$$p_{ij} = \frac{\exp\left(v_{ij}\right)}{\sum_{l \in D_i} \exp\left(v_{il}\right)}$$

where D_i denotes the choice set in case i. Hence, the log likelihood can be expressed as

$$\ln L = \ln \prod_{ij} p_{ij}^{\mathbb{I}_{\{y_i=j\}}} = \sum_{ij} \mathbb{I}_{\{y_i=j\}} \left[v_{ij} - \ln\left(\sum_{l \in D_i} \exp\left(v_{il}\right) \right) \right].$$

The model was estimated using maximum likelihood in Stata SE 14.2 (StataCorp, 2015). The variables used in the model are summarized in Table D.4.

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 (Swait and Louviere, 1993) to control for the different origin of the two (partial) data sets nor was it possible to take into account panel effects (Hole, 2007). From a behavioral standpoint, the limitations

7 On the case level, the $\mathbf{x}_{ij}'$ form a $J \times r$ matrix $\mathbf{X}_i$. Moreover, the γ_j can be written as a $q \times J$ matrix $\mathbf{A} = \left(\gamma_1, ..., \gamma_J\right)$. Then, the utility function can be rewritten as

$$\mathbf{u}_i = \mathbf{X}_i \boldsymbol{\beta} + \left(\mathbf{z}_i \mathbf{A}\right)' + \boldsymbol{\epsilon}_i = \left(\mathbf{X}_i, \mathbf{z}_i \otimes \mathbf{I}_J\right) \begin{pmatrix} \boldsymbol{\beta} \\ \operatorname{vec}\left(\mathbf{A}'\right) \end{pmatrix} + \boldsymbol{\epsilon}_i = \mathbf{X}_i^* \boldsymbol{\beta}^* + \boldsymbol{\epsilon}_i.$$

Now, following Cameron and Trivedi (2009), a cluster-robust estimator of the variance-covariance matrix of the estimators is given by

$$\widehat{\mathbf{V}}_{\text{cluster}}\left(\widehat{\boldsymbol{\beta}}\right) = \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1} \left(\frac{G}{G-1} \frac{N-1}{N-k} \sum_t \mathbf{X}_g^* \widehat{\mathbf{u}}_g \widehat{\mathbf{u}}_g' \mathbf{X}_g^{*\prime} \right) \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1},$$

where $g = 1, ..., G$ denotes the cluster (in this case person ID), $\widehat{\mathbf{u}}_g$ is the vector of residuals in the gth cluster and $\mathbf{X}_g^*$ is a matrix of the regressors for the observations in the gth cluster.

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 D.4: List of Attributes for mode choice model

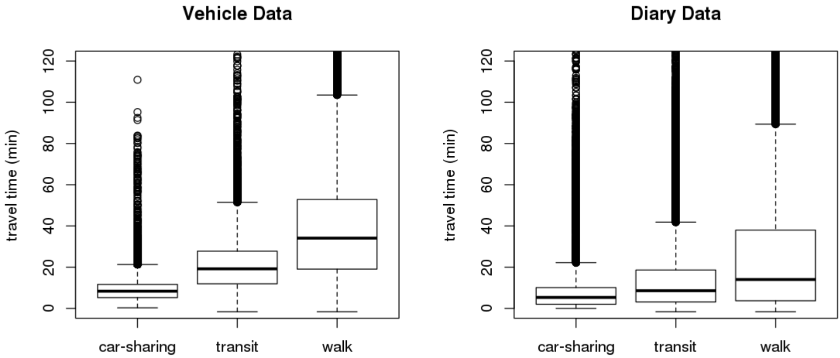


FIGURE D.4: Distribution of travel times for the three modes (routed trips).

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 (Becker et al., 2017a).

D.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 D.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 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 D.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 (Hausman and McFadden, 1984) has been used to test the consistency of the two models. With a $\chi^2 = 122.44$ ($df = 20$, $p < 0.001$) 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 D.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[8], which is comparable to results from earlier studies in Switzerland (Hess et al., 2008). 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 (Hess et al., 2008). 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 $5\,\text{km/h}$ (Dal et al., 2009) 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

8 In the model for the extended choice set, the values are 10 CHF and 29 CHF. However, given the large confidence bands (Oehlert, 1992) of these elasticities, the differences are not significant.

	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 ****						

TABLE D.5: Mode choice model: multinomial logit model with alternative specific constants and clustered standard errors.

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.

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.

D.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 (Schmöller et al., 2015). 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 (Kang et al., 2016). 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. (2015), 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 (de Lorimier and El-Geneidy, 2013).

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 (Celsor and Millard-Ball, 2007; Stillwater et al., 2009).

The results also show that customers are willing to accept a substantially longer access walk to the car-sharing vehicle than for public transportation. This is in line with findings from a stated-preference survey on demand-adaptive transit (Frei et al., 2017), where the authors found that waiting at the trip origin (e.g. at home) is perceived less burdensome than waiting at a bus stop. In the case of free-floating car-sharing, it can be argued that the additional walk is usually made up for by a shorter overall travel time. Moreover, at the end of the access walk to a free-floating car-sharing vehicle, the customer can directly board the car, as opposed to public transport, where there may be an additional wait for a delayed bus. 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 (Schmöller et al., 2015), 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 (Stopher, 1980). 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 (Becker et al., 2017a). Moreover, a comparison of the two models presented in Table B.4 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.

D.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 (Horni et al., 2016) 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.

ACKNOWLEDGEMENTS

This research is part of a Swiss National Fund project (National Research Program 71: Managing Energy Consumption, project number 407140_153807). We also thank Mobility Switzerland and the Canton of Basel-Stadt for their support. The paper has benefitted substantially from the comments of Basil Schmid and two anonymous reviewers.

E

ASSESSING THE WELFARE IMPACTS OF SHARED MOBILITY AND MOBILITY AS A SERVICE (MAAS)

This paper has been published as: Becker, H., M. Balac, F. Ciari and K. W. Axhausen (2019) Assessing the welfare impacts of MaaS: A case study in Switzerland, *Transportation Research Part A*. DOI: 10.1016/j.tra.2019.09.027

ABSTRACT

Mobility as a Service (MaaS) is an attempt to overcome market segmentation by offering transport services tailored to the individual traveler's needs. An alternative to prior investment into single mobility tools, it may allow less biased mode choice decisions. Such a setting favors shared modes, where fixed costs can be apportioned among a large number of users. In turn, car-sharing, bike-sharing or ride-hailing may themselves become efficient alternatives to public transport. Although early field studies confirm the expected changes away from private car use and towards public or shared modes, impacts are yet to be studied for larger transport systems. This research conducts a first joint simulation of car-sharing, bike-sharing and ride-hailing for a city-scale transport system using MATSim. Results show that in Zurich, through less biased mode choice decisions alone, transport-related energy consumption can be reduced by 25 %. In addition, introduction of car-sharing and bike-sharing schemes may increase transport system energy efficiency by up to 7 %, whereas the impact of ride-hailing appears less positive. Efficiency gains may be higher if shared modes were used as a substitute for public transport in lower-density areas. In summary, a MaaS scheme with shared mobility may allow to slightly increase system efficiency (travel times & cost), while substantially reducing energy consumption.

CONTRIBUTIONS

The study was designed by H. Becker and M. Balac. M. Balac developed the bike-sharing extension for MATSim, implemented the subsidy functionality and prepared the simulation framework for this research. H. Becker conducted the literature review, prepared the behavioural models, defined the scenarios and analyzed the simulation results. Both H. Becker and M. Balac interpreted the results and prepared the manuscript. F. Ciari and K.W. Axhausen supervised the work and provided feedback at various stages.

E.1 introduction

In current transport systems, short-term travel behaviour is to a large extent governed by long-term choices of mobility tool ownership. Such mobility tools usually require a substantial investment up-front and subsequently allow to travel with the specific modes at low (or zero) marginal cost. Eventually, distinct mobility portfolios arise dividing a population into car drivers and transit riders (Becker et al., 2017c).

The concept of *Mobility as a Service* (MaaS) aims to break the determining role of car ownership. Instead, travelers are presented a variety of travel options tailored to their respective needs, either as a subscription package or in a pay-per-use approach, by an integrated mobility provider (Kamargianni et al., 2016; Jittrapirom et al., 2017; Mulley, 2017). Consequently, short-term mode choice decisions are driven by the actual cost of use (instead of fixed/sunk costs biasing decisions to a certain mode), which allows for a more time- and cost-aware travel behaviour - an observation already made for early car-sharing customers (Cervero and Tsai, 2004). More recently launched shared mobility services already point into this direction: Uber, Bridj, car2go as well as many others do not charge membership fees, but follow a pay-per-use approach. However, it is unknown if they currently charge their average cost per km (including overheads and profit margins).

In the past years, there were first attempts to transfer this concept to private cars and public transport, and thus turn travellers into mobility consumers. For example, Sochor et al. (2015, 2016) conducted a six-month field test in the city of Gothenburg, Sweden, in which participants could purchase a monthly credit for the use of individual cars, car-sharing and public transport. Using one-week travel diaries, they show that participants generally over-estimated their actual travel demand and that as MaaS users, they would substantially reduce their use of individual cars and increase their use of public transport instead.

However, it is still unclear how to re-design a whole transport system to reap these benefits of MaaS shown in small-scale field tests. In particular, this will require changes in the supply side of the system, i.e. restructuring public transport services (Hensher, 2017) and integrating them with novel systems of shared mobility (Cervero, 2017). On the demand side, the first insights from field tests have to be generalized to learn more about the preferences of travellers in such integrated mobility systems (Matyas and Kamargianni, 2017). Indeed, differences observed between Uber riders and taxi customers or users of different car-sharing schemes indicate that even small changes in the service types may attract different customer segments (Rayle et al., 2016; Becker et al., 2017a).

Following the approach suggested by Ciari and Becker (2017), a framework to assess the impact of supply side characteristics of a potential MaaS scheme on the transport network is developed in this research. Variables include type and fleet sizes of shared modes, their integration with public transport and additional taxes on car travel. Target indicators are generalized cost (welfare) measures, total network travel times and total energy consumption. The framework is applied to the city of Zurich, Switzerland. The aim of this research is to provide some first simulation-based evidence on possible system-level impacts of large-scale MaaS schemes and the role shared mobility can play in such an integrated service. The results may help to generate additional research to provide more detailed analyses of relevant aspects.

E.2 BACKGROUND

For almost a century, private cars have dominated transport systems in industrialzied countries around the globe, by far outnumbering any form of collective transportation. A main reason for this (among various others) is that accessibility levels by public transport are usually substantially lower than those by car - even in Switzerland, which arguably has one of the best public transport offerings worldwide, there is a 35% difference (Axhausen et al., 2011). Whilst in dense cities, bundling passengers in buses or trains allows to increase system capacity (Loder et al., 2017), such bundling is not feasible in low-density neighborhoods or countrysides and usually results in long headways and/or stop-spacing. In such situations, demand-responsive transit services (Mulley and Nelson, 2009) may help to extend public transport networks, although no large-scale implementations have been tested yet.

In recent years, numerous new mobility services have emerged, such as bike-sharing (Fishman, 2016), car-sharing (Shaheen and Cohen, 2013) or ride-hailing services like Uber. They mostly operate in urban areas and often attract public transport users, thus also having a potential of extending public transport networks by offering last-mile connections (Fishman et al., 2014a) or fast tangential trips (Becker et al., 2017b). However, currently, most such schemes are operated independently from each other and from collective transportation, so that reaping such benefits cannot be guaranteed.

MaaS aims to combine existing modes of collective transportation with such emerging services to establish a more attractive alternative to the private car (Kamargianni et al., 2016; Jittrapirom et al., 2017; Mulley, 2017). A twofold integration will be required to achieve this goal:

- integrated strategic and operational planning across all mobility services (i.e. network / service areas, fleet sizes, fare integration),
- integrated user interface, through which all services can be accessed and booked.

While the first part is obviously required to offer a seamless mobility solution, the second part allows travelers to make informed (and therefore better) decisions.

Sochor et al. (2015, 2016) conducted a first field test of a MaaS scheme with an emphasis on the second part (integrated user interface). In their study, participants purchased credit for the use of different mobility services, which they could then book through a unified service center. The results indicate that participants typically over-estimated their need for private car use. This is in line with an observation made for car-sharing customers, who often switched to a public transport lifestyle and use car-sharing vehicles for far less trips than they previously used their car for (Cervero and Tsai, 2004). Such observations point at one key behavioral implication of MaaS: Current transport modes are typically dominated by fixed costs (Becker et al., 2017c; Bösch et al., 2018), so that acquisition of a mobility tool often predetermines later mode choice (because of the low marginal costs). MaaS overcomes the separation of fixed (sunk) and marginal costs by a pay-per-use approach. This way, it enables travelers to take unbiased and hence, more suitable mode choice decisions.

Yet, the user interface and cost transparency are only two ways, through which MaaS contributes to a more efficient transport system. The second way lies in a supply-side integration. Various forms of organizational and contractual frameworks have been proposed to accomplish this integration whilst maintaining certain levels of autonomy for the individual operators (Ambrosino et al., 2016; Hensher, 2017; Smith et al., 2018). However, the question of which particular systems to include in an effective MaaS offering has not been addressed yet.[1] Moreover, it is still unclear, to what extent they could even substitute current line-based public transport services (Hensher, 2017).

Various new mobility services have emerged in the past years, ranging from dynamic ride-pooling services like *Via*[2] in New York City to electric bike-sharing like *Smide*[3] in Zurich. Given the novelty and variety of such schemes, there is only limited knowledge about their overall impacts on the transport system. Moreover, insights gained about one scheme cannot necessarily be transferred to others. For example, it has been established that station-based (round-trip) car-sharing schemes leverage a reduction in their members' vehicle ownership and vehicle miles traveled (Cervero and Tsai, 2004). For free-floating car-sharing, such impacts were found to be substantially weaker, because this structually different service attracts other user groups and usage patterns (Becker et al., 2017a). Also for ride-hailing, Rayle et al. (2016) found the user types and demand patterns to be different from taxi riders. Moreover, differences do not only appear between schemes, but also between cities. For example, Fishman et al. (2014a) suggest that the ecological impact of bike-sharing strongly depends on city characteristics. They found that while bike-sharing may help to reduce CO_2 emissions in car-centered cities, they may even trigger an increase in transit-oriented cities. Also, such schemes will likely be used differently when integrated with public transportation: As shown by Wang and Ross (2017) for the case of New York City, taxi trips made in connection with a public transport trip are typically shorter and are done by lower income users than point-to-point taxi trips. However, there have hardly been any empirical results on the interrelations between the different emerging mobility services yet.

Instead, simulation-based and game-theory approaches have mostly been used to study interactions of emerging modes. For example, Djavadian

1 Aiming for maximum attractiveness, Mulley (2017) suggests to include all available modes.
2 `https://ridewithvia.com/`
3 `https://www.smide.ch/`

and Chow (2017) modeled a MaaS scheme offering first/last mile services. Their results reveal the existence of stable local optima for fleet sizes and fares. Those findings extend earlier research by Li and Quadrifoglio (2010), who define critical demand levels below which demand-responsive services serve demand more efficiently. Generalizing these insights to maximizing social welfare instead of minimizing operational costs, Kim and Schonfeld (2015) presented an approach to define a welfare threshold between conventional and flexible services in systems with multiple dissimilar regions. The welfare-centric approach was also supported by Qiu et al. (2018), who suggest that minima of monetary cost may not correspond to a transport system-level optimum given that also MaaS fleets contribute to road congestion. For the case of ride-sourcing schemes, Zha et al. (2016) even found that a welfare-optimum state could only be reached if competitors were forced to merge and subsequently be regulated.

For the case of shared mobility, optimization has mostly been performed with respect to profit. Jorge and Correia (2013) and Li et al. (2018) provide an overview of such approaches, which mostly addressed fleet sizes, station locations, service areas, reservation policies or relocation strategies for car-sharing services. Similar approaches have been developed for bike-sharing (Raviv et al., 2013). However, most of such optimization approaches have substantial limitations, such as a small study area, no load-dependent travel times or fixed demand. Moreover, the individual emerging modes have usually been studied in an isolated manner. To address those limitations, Ciari et al. (2015b) simulated free-floating car-sharing as part of the transport system using the agent- and activity-based transport simulation MATSim (Horni et al., 2016). In particular, this allows to study substitution effects with other modes (private car, schedule-based public transport, bike and walk). Although this approach does not allow mathematical optimization of a target function, it allows to perform a scenario-based analysis to identify plausible, near-optimal solutions. Also, MATSim has recently been extended to model automated taxi services (Hörl, 2017) or competing operators of shared mobility (Balac et al., 2019).

In this research, MATSim is further extended to allow a first joint simulation of large scale car-sharing, electric bike-sharing and ride-sourcing schemes to study their interactions with each other as well as with the existing transport system. Also, a potential integration with line-based public transportation including a subsidy framework is tested. The various scenarios are then used to understand, how large fleets of shared modes could contribute to welfare and resource efficiency of the transport system. This way, the potential efficiency gains of the strategic and operational integration aspect of MaaS (step 1) are studied, assuming that the integrated user interface (step 2) is already in place.

The approach is applied to the greater Zurich area. Zurich presents a special case, because it not only has a highly-developed public transport network reaching a 32% mode share[4]. In addition, a number of conventional and electric bike-sharing schemes as well as an electric scooter-sharing scheme have been launched in the recent years, complementing the already existing station-based car-sharing scheme called Mobility[5]. Also Uber is already present in the market with its UberX, UberBlack and UberGREEN services. Hence, Zurich already is a test-lab for diverse emerging mobility services, none of which, however, is integrated with the public transport providers.

E.3 METHODOLOGY

In this research, the agent-based microsimulation tool MATSim (Horni et al., 2016) is used to simulate use of MaaS services in the city of Zurich. In MATSim, a synthetic population of agents aims to pursue their desired daily activities whilst trying to minimize their generalized cost of travel. Agents' choice dimensions include the transport mode and route for each trip. A key advantage of MATSim is that it offers a dynamic demand response towards changes in service attributes such as travel times or costs. Agents have pre-defined (fixed) levels of mobility tool ownership (cars, season tickets and car-sharing membership), which reflect the current distribution in the local population.[6] In the standard model, cars, public transport (timetable-based and routed), bike and walk are available modes. For this research, car-sharing services are added using earlier work of Balac et al. (2015, 2017, 2019) and a plugin for autonomous taxis (Hörl, 2017) is

4 for trips within the city of Zurich, according to Planungsbüro Jud (2012) Städtevergleich Mobilität `https://skm-cvm.ch/cmsfiles/130124_stadtevergleich_mobilitat.pdf`

5 `https://www.mobility.ch/en/`

6 Note that current MATSim does not allow agents to change their portfolio of mobility tools, nor their home or work locations. In this research, a fixed level of car-ownership means that the actual VMT reduction impact of shared modes may be higher than reported in the results.

used to simulate ride-hailing services. In addition, a framework to simulate free-floating electric bike-sharing services was implemented for this research (see E.7). To the authors' best knowledge, this is the first time that these different modes of shared mobility are jointly simulated not only in MATSim, but in any agent-based model.

E.3.1 *Implementation of Shared Modes*

All shared services are simulated on a microscopic level. Hence, the number of available vehicles (supply) is both limited and time- and space-dependent. For bike-sharing and car-sharing trips, agents identify the closest available vehicle, which they subsequently access by walk. The trip is routed on the congested network (car-sharing only). At the end of the trip, the shared bike or car is parked at the agent's destination. Availability of vehicles at the trip start time is recorded to inform re-planning decisions in the following iterations (see below for details). A detailed presentation of the car-sharing framework is provided by Balac et al. (2019). The implementation of the bike-sharing framework is described in E.7. Agents using the ride-hailing service wait at their origin to be picked up by the closest available ride-hailing vehicle. The actual waiting time is stored and used in the later iterations to estimate the expected waiting time at the specific location. After being picked up, the agent is driven on the congested network to its destination, where it is dropped off. The vehicle remains at the drop-off location until it is dispatched to serve a new customer. Details are provided by Hörl (2017).

Although MATSim's shared-mobility extensions allow to assign membership to specific subgroups of agents for shared modes, in this research it is assumed that all agents have access to all (shared) modes, irrespective of any memberships.[7] Following general practise, car-sharing and electric bike-sharing are only considered available for agents holding a driver's license. Shared modes are available for all trips within a pre-defined service area. In this research, the service area covers the city of Zurich as well as a small belt around it (including the airport). It is shown in Figure E.1. The area has around 380 000 residents of which about 280 000 hold a drivers

7 For most free-floating schemes, this is already the case given that they only charge a small registration fee. For ride-hailing services users can usually sign up for free.

license. Initial positions of bike-sharing, car-sharing and ride-hailing vehicles were drawn randomly from the population density distribution within the service area.

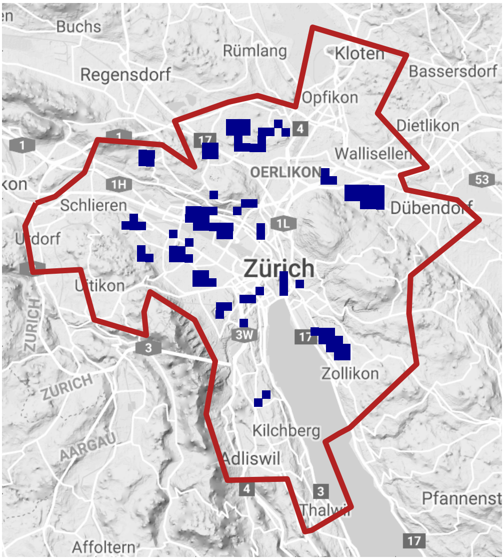


FIGURE E.1: Service area for shared modes. Blue zones denote areas eligible for subsidies (see Section E.4 for details). Background map by Google Maps (`maps.google.com`).

Fares are based on current implementations of free-floating car-sharing, free-floating e-bike-sharing and ride-hailing in Switzerland and are calculated as follows:

- *Car-sharing:* $0.38\,\text{CHF}/\text{min} \cdot t$
- *Bike-sharing:* $0.25\,\text{CHF}/\text{min} \cdot t$
- *Ride-hailing:* $\max\{6.0\,\text{CHF}; 3.0\,\text{CHF} + 1.8\,\text{CHF}/\text{km} \cdot d + 0.3\,\text{CHF}/\text{min} \cdot t\}$

where t is the travel time in minutes and d is the in-vehicle distance in kilometers. Of course, larger fleet sizes and integration with other (shared) modes may result in different fares. However, to limit complexity, fares were assumed fixed in this research.

As a comparison: public transport fares in MATSim are 0.36 CHF/km, with season tickets reducing this fare by 50 % or 100 %.[8] For car trips, a perceived (marginal) cost of 0.27 CHF/km is assumed following Hörl et al. (2018b). This value does not include any fixed cost (not considered in MATSim), but only the perceived cost of car travel relevant in mode choice.

E.3.2 *Mode Choice*

The MATSim simulation follows an iterative process, in which after each iteration, a certain number of agents are allowed to change their mode and/or route to reduce their generalized cost of travel (re-planning). At this stage, a discrete mode choice extension for MATSim is used in the re-planning phase to allow for mode-choice decisions.[9] Agents chosen for re-planning are allowed to change their modes of travel on a tour level by using an MNL mode-choice model (introduced below). The discrete mode choice extension makes sure that only feasible mode chains are possible (e.g. car-transit-car mode chain is not feasible as an automobile needs to be available for the second car trip). Benefits of using en estimated mode-choice model and how it was integrated in the re-planning phase of the MATSim loop can be found in Hörl et al. (2018a, 2019).

To the authors' best knowledge, no mode choice models exist yet, which cover all seven modes simulated in this research. Therefore, mode choice parameters are based on a recent stated-preference experiment on automated vehicles (Hörl et al., 2018b). The general form of the utility for mode m is:

$$\begin{aligned} U_m = \alpha + \beta_{tt,m} \cdot tt_m + \delta_{m=cycling} \cdot \beta_{age} \cdot (\text{age} - 18) + \\ \beta_{access,m} \cdot tacc_m + \delta_{m=PT} \cdot \beta_{transfers} \cdot \#transfers_m + \\ \beta_{cost,m} \cdot \left(\frac{dist}{40\,\text{km}} \right)^{\lambda} \cdot cost_m \end{aligned} \quad (E.1)$$

Since the mode choice model described in Hörl et al. (2018b) does not include services like bike-sharing, car-sharing and ride-hailing, the respective mode choice parameters were defined as follows: For the valuation

8 The simulation does not exactly model the zone-based fare system, which actually is in place. Instead, fares are broken down into marginal cost while roughly maintaining the same level of average fares.

9 www.eqasim.org

of travel time of bike-sharing and car-sharing, the respective parameters for bike and car were used. This is motivated by earlier research of Li and Kamargianni (2018) who show this equivalence using survey data for a Chinese context. For ride-hailing, half of the value for public transport was used to account for the increased level of comfort and privacy.[10] For all shared modes, access walk parameters were assumed to be equal to public transport access walk parameters. This also corresponds to results of earlier research (compare Li and Kamargianni (2018) and Miguel Martinez et al. (2017)). Waiting time for ride-hailing was assumed 50 % of the corresponding parameter for public transport (motivated by Frei et al. (2017)).

Alternative-specific constants were used to calibrate the number of daily rentals per vehicle in the base case. For free-floating car-sharing around 5 rentals per vehicle are assumed for small fleet sizes (compare Habibi et al. (2017)). For bike-sharing 6-8 rentals per bike were assumed realistic for Zurich.[11] Finally, based on taxi data from New York City, up to 35-40 daily rentals per vehicle were assumed realistic for a highly utilized ride-hailing scheme.[12] All resulting mode choice parameters used in this research are summarized in Table E.1.

It should be noted that such a combination of partial mode choice models may only have limited validity. Hence estimating a dedicated choice model based on empirical data capturing all those modes simultaneously would be a superior approach. In both cases, a sensitivity-analysis could help to account for potential changes in behavior or errors in the model. However, in this research such a sensitivity analysis had to be omitted due to the high computational burden associated with it.

E.3.3 *Cost Structures*

To allow economic analysis of the schemes, their respective cost structures were estimated using the framework of Bösch et al. (2018). The values are presented in Table E.2. Fixed and variable vehicle cost for car-sharing

10 To the authors' best knowledge, no earlier research is available which would allow a more accurate assumption. Anyway, implications on the results are minor since the utility function of ride-hailing is dominated by the fare component.

11 https://edition.cnn.com/travel/article/bike-share-boom-global-report/index.html

12 http://toddwschneider.com/posts/taxi-uber-lyft-usage-new-york-city/

	Walk	Bike	Car	PT	FFCS	FFBS	Ride-hailing
constant	0.631	0.344	0.827		-0.300	-0.300	-0.300
travel time [min]	-0.141	-0.080	-0.067	-0.019	-0.067	-0.080	-0.010
age (> 17)		-0.049				-0.049	
access walk [min]				-0.080	-0.080	-0.080	
waiting time [min]				-0.038			-0.019
number of transfers				-0.170			
cost [CHF]				-0.126			
λ				-0.400			

TABLE E.1: Mode choice parameters for conventional modes (left) (Hörl et al., 2018b) and assumptions for shared mobility (right).

and ride-hailing are derived from Bösch et al. (2018) for the case of conventional midsize vehicles operated as a shared fleet. For ride-hailing, the variable vehicle cost is increased by 15 % compared to car-sharing to account for empty rides (Bösch et al., 2018). For bike-sharing, fixed cost were assumed to equal the retail price of the cheapest Stromer e-bike, minus 25 % discount, written off over 5 years with 200 business days per year. This roughly corresponds to the current system characteristics of the local e-bike sharing scheme Smide in Zurich. For the variable costs, a product test revealed maintenance cost of 0.135 CHF/km for private customers, off which 25 % discount was subtracted for larger fleets (economies of scale).[13] Overhead and management cost were used from Bösch et al. (2018), but reduced by 50 % for e-bikes.[14] For ride-hailing services, it is assumed that each vehicle is driven for 14 hours[15] with a gross salary of 20 CHF/h.[16]

E.3.4 *System-level analyses*

To allow an evaluation of the system-level impacts of the MaaS services, all scenarios are evaluated with respect to three key indicators:

- **total network travel time**: sum of travel times of all trips
- **generalized cost**: sum of the (dis-)utility of all performed trips (c.f. Equation E.1), to which profits or losses of shared mobility operators as well as subsidies paid for public transport services are added. For private car travel, the full costs are considered in all cases.[17]
- **total energy consumption**: distance of all trips multiplied with an energy consumption factor. For private cars, an average gasoline consumption of 6.5 l/100km was assumed.[18] Car-sharing vehicles operating in Basel and Geneva are VW up with an official consumption

13 `https://www.ktipp.ch/artikel/d/e-bikes-pannen-trueben-den-fahrspass/`

14 Bike-sharing schemes usually supply more bikes per member, so that user administration cost per bike is lower (compare Zhao et al. (2014)). In addition, bikes are easier to collect when service is required.

15 There may actually be more than one driver per vehicle.

16 This roughly corresponds to the salary of newspaper delivery workers (compare `https://www.srf.ch/sendungen/kassensturz-espresso/themen/arbeit/zeitungsvertraeger-so-schlecht-zahlt-die-post`).

17 For *Scenario 1*, the hidden cost was added to the disutility.

18 for fuel consumption data of new car registrations compare `http://www.verbrauchskatalog.ch/de/informationen/verbrauch`

	Bike-Sharing	Car-Sharing	Ride-Hailing
fixed vehicle cost (CHF per veh. / day)	4.1	8.5	8.5
variable vehicle cost (CHF per km)	0.101	0.223	0.256
overhead & management cost (CHF per veh. / day)	7	14	14
driver's salary (CHF per veh. / day)			280

TABLE E.2: Cost structures of Shared Mobility Services.

of 4.1 l/100km. For electric bikes, a consumption of 1 kWh/100km is assumed.[19]. For public transport, the total energy consumption reported by the local bus and tram provider was used.[20] Fuel consumption was converted into energy at 9.7 kWh/l.

For the system-level analyses, all trips conducted within the service area (compare Figure E.1) are considered, including those made by public transport or private car.

E.4 SCENARIOS

The main goal of this research is to study how a large-scale MaaS system could help to increase efficiency of the transport system. To this end, walk, bike, private car, public transport, electric bike-sharing, car-sharing and ride-hailing are all available to agents at their marginal cost. This way, mode choice is assumed unbiased from fixed / sunk costs, theoretically yielding more optimal results.

Hence, no subscriptions are considered for any of the shared modes. Only for public transport, season tickets are still in place. For the private car, only marginal costs are considered. Here, two cost levels were analyzed: First, the marginal cost of car travel was set to the currently perceived costs (0.27 CHF/km), while in a second step, the full costs according to Bösch et al. (2018) are assumed relevant for the agents' mode choice decisions (0.64 CHF/km)[21].

Since the impact of shared mobility schemes may depend on their respective fleet sizes, different scenarios have been defined covering all combinations of the set fleet sizes:

- *Car-sharing:* 0, 250, 1 000, 4 000, 8 000
- *Bike-sharing:* 0, 250, 1 000, 4 000, 8 000
- *Ride-hailing:* 0, 250, 500, 1 000, 5 000

19 compare `https://www.stromerbike.com/en_INT/e-bikes/st5.html`

20 VBZ business report for 2017: `https://www.stadt-zuerich.ch/vbz/de/index/die_vbz/geschaeftsbericht.html`

21 In this context, the full cost include acquisition cost, fuel, vehicle maintenance, insurance, taxes, administration and any other expense related to private car ownership and use.

The fleet sizes were chosen to cover all possible implementations from small fleets towards multiples of today's number of vehicles. For example, Uber claims to have 2 500 drivers at their service across all of Switzerland as of July 2018.[22] Moreover, about 1 800 shared bikes were available in the city of Zurich in early 2018.[23] Free-floating car-sharing is currently not available in Zurich, however, in other Swiss cities schemes operate with up to 150 vehicles.[24] Fleets smaller than 250 vehicles were not simulated for computational reasons.[25] Simulations included a baseline case with zero fleet size for all three shared modes.

In the first part of the analysis, impacts on transport system performance are studied for all combinations of fleet sizes using the perceived costs for private cars (*Scenario 1*). Second, the analysis is repeated for the full cost of private cars (*Scenario 2*). Each of the scenarios is then evaluated with respect to total generalized cost, total network travel times and total energy consumption.

Yet, shared modes may not only increase system performance by complementing existing modes, but in certain situations, they may also represent an efficient substitute. To test this hypothesis, the 25 bus and tram lines operating in the city of Zurich with a fare recovery rate of less than 75 % were removed.[26] This would amount to (hypothetical) savings of more than 200 000 CHF per day. In those areas, for which the distance to the next served public transport stop is increased by more than 50 m through this measure, use of shared mobility is subsidized as follows:

- subsidies are paid for any trip starting or ending in an eligible zone,
- ride-hailing trips are subsidized with 50 % of the fare,

22 https://www.nzz.ch/schweiz/chef-von-uber-schweiz-haelt-fest-fahrer-wollen-nicht-angestellt-s 1403722
23 https://www.nzz.ch/zuerich/publibike-lanciert-den-heissen-zuercher-mietvelo-sommer-ld. 1374926
24 https://www.catch-a-car.ch/en/home/
25 To limit computation time to a feasible level, only a 10 % sample of the population was simulated in the model. While network capacities could be scaled down proportionally, this was not possible for shared mobility fleets. Here, only 10 % of the fleet were simulated. While this approach has been widely used for medium to large fleets (compare Balac et al. (2015, 2017)), it may yield unreliable results for very small fleets.
26 compare https://www.kantonsrat.zh.ch/Dokumente/Df49fc539-2ea1-4654-98df-68d694fec079/ R15301.pdf

- those portions of bike-sharing or car-sharing fares, which exceed the corresponding public transport fare are subsidized by 100 %, i.e. travelers only pay rental charges up to the fare of the alternative (removed) public transport service.

To identify zones eligible for subsidies, the city was divided into 250 m grid cells. Figure E.1 highlights the cells eligible for subsidies.

Of course, such a rough approach can only provide very first insights. In particular, it is well conceiveable that removing a public transport line will affect the productivity of various remaining lines. As a result, an optimal public transport network subject to the budget contraint stated above may likely look different.

E.5 RESULTS

More than 150 single scenarios were simulated in MATSim. For brevity, only a selection showing the key insights from the analyses is presented in this paper. The full set of results is available from the authors upon request.

In the following, *Scenario 1* denotes all simulations, where the cost for private car travel was set to 0.27 CHF/km, i.e. the perceived cost level. In *Scenario 2*, this value was set to 0.64 CHF/km, which corresponds to the full costs.

E.5.1 *Competition of Shared Modes*

The first part of the analysis allows insights on the interactions and competition between the shared modes. To this end, Figure E.2 shows their number of rentals.

The results indicate that for each shared mode in Scenario 1, there is a saturation effect for larger fleet sizes. Hence, despite increasing availability of the respective service, utilization of the vehicles drops after a certain point. The simulation results suggest optimal fleet sizes of around 1 000 vehicles for car-sharing and bike-sharing, and at most 250 vehicles for ride-hailing. Yet, given the limited number of scenarios, the true optimal values may likely be slightly higher or lower than indicated here.

The figure also provides insights into the competition between the shared modes. For example, it shows that demand for car-sharing and bike-sharing is affected by the fleet sizes of the other schemes. However, with a relative difference of up to 10 %, the demand impacts through competition are not substantial. Still, a certain pattern can be observed: presence of small car-sharing and ride-hailing fleets increases demand for bike-sharing, whereas competition by large car-sharing fleets reduces it. In contrast, presence of a small bike-sharing scheme lowers demand for car-sharing, but larger bike fleets increase it. Interestingly, ride-hailing demand seems to be independent from competition of other shared modes.

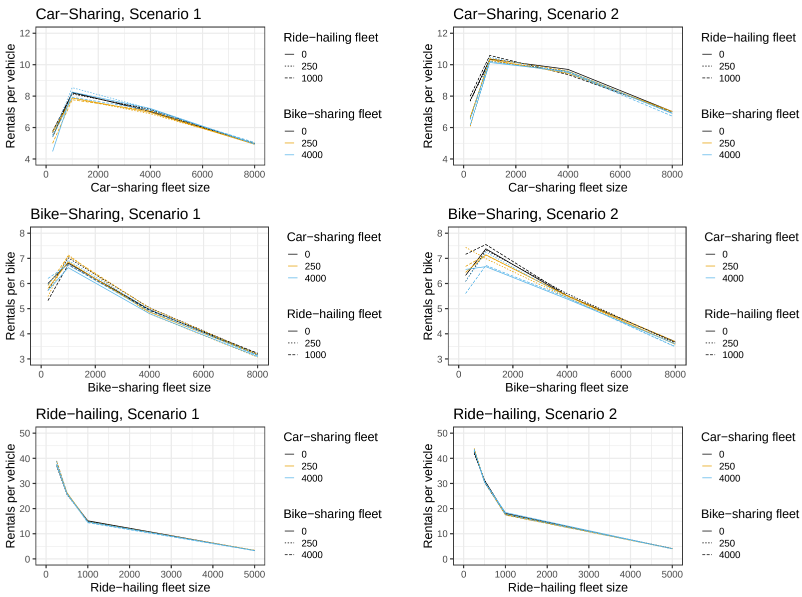


FIGURE E.2: Number of rentals for shared modes. Line color and shape denote composition of shared fleet.

Yet, presence of other shared modes in the market does not seem to substantially alter the structure of demand. Table E.3 presents the access times and network distances. The standard errors are mostly less than 5 % of the reported means. Also the trip distances are mostly independent of the fleet sizes of the different services. Only the access times are lower for larger fleets, with the strongest effect observable for ride-hailing with a 60 % reduction in wait times when the fleet increases from 250 to 1 000 vehicles.

Service	Fleet	Access time [min]		Trip distance [km]	
		Scenario 1	Scenario 2	Scenario 1	Scenario 2
Car-sharing	250	3.67	3.74	4.57	5.05
	1 000	3.47	3.49	4.52	5.07
	4 000	2.73	2.80	4.42	5.04
	8 000	2.09	2.20	4.45	5.08
Bike-sharing	250	3.70	3.64	1.83	2.31
	1 000	3.36	3.42	1.95	2.20
	4 000	2.49	2.54	1.90	2.22
	8 000	1.87	1.91	1.88	2.19
Ride-hailing	250	9.09	9.56	3.48	3.69
	500	4.04	4.26	3.44	3.67
	1 000	3.69	3.74	3.43	3.66
	4 000	1.91	1.90	3.46	3.67

TABLE E.3: Mean access times [min] and mean network distances [km] of trips. Access times are walk time for car- and bike-sharing and wait time for ride-hailing.

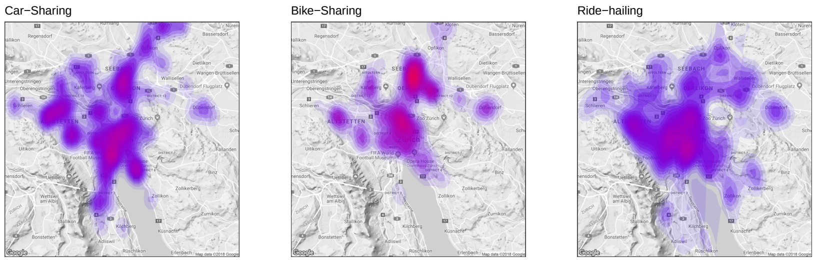
Although trip distances are fairly constant throughout all scenarios, the spatial distribution of start locations varies substantially, as shown in Figure E.3. For example with a small fleet size, bike-sharing start locations are quite concentrated to certain spots in the city center and the northern sub-center Oerlikon. When car-sharing and ride-hailing enter the market, the concentration is even more focused to the North, where the other services are less strong. Only at very large fleet sizes the distribution becomes more continuous and centered towards the city center. Also for car-sharing, demand is more disperse without competition. For small fleets and with competition, it is focused on the city center, while larger fleet sizes lead demand to spread more into outer parts of the city. Interestingly, for case (b), car-sharing demand and bike-sharing demand appear to complement each other with demand peaks in different parts of the city. In contrast to bike- and car-sharing, ride-hailing demand follows a similar demand distribution throughout all scenarios. A reason for this may be that ride-hailing vehicles can move towards their clients at higher speeds, increasing local availability of the service. For the same reason, car-sharing demand distribution approaches the one of ride-hailing for very large fleets.

The results suggest that free-floating car-sharing and electric bike-sharing compete over similar demand hot spots, whereas ride-hailing serves a different demand segment. The key drivers of this segmentation are the conveniece of access as well as fares (also compare Table E.1). Moreover, the speed difference of cars and electric bicycles is relatively small, at least during peak hours. Although Figure E.3 even suggests a certain overlap between free-floating car-sharing and electric bike-sharing demand, their trip distances are substantially different. There are also features which the simulation model cannot capture: For example, car-sharing allows users to transport larger items, which is an important factor for a certain number of trips (Becker et al., 2017a).

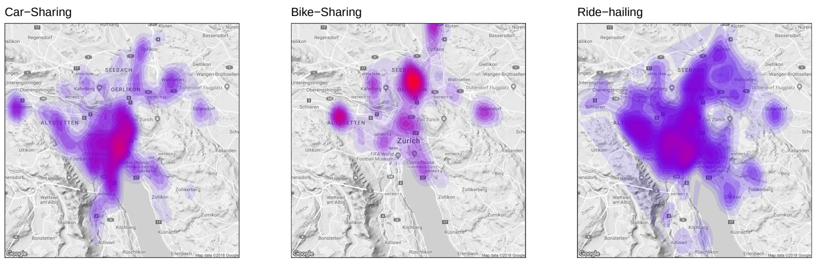
E.5.2 *Profitability of Shared Modes*

Using the fares and cost structures outlined in Section E.3, the profit of each operator was determined for all scenarios. The results are presented in Figure E.5. They indicate that in *Scenario 1*, bike- or car-sharing services cannot be operated at a profit. However, losses are only a few CHF per vehicle per day and are lowest for fleets of 1 000 vehicles each. Interestingly, car-sharing profits are reduced in the presence of a small bike-sharing scheme (fleet size 250), whereas bike-sharing profits are reduced in the presence of a large car-sharing scheme (fleet size 4 000).

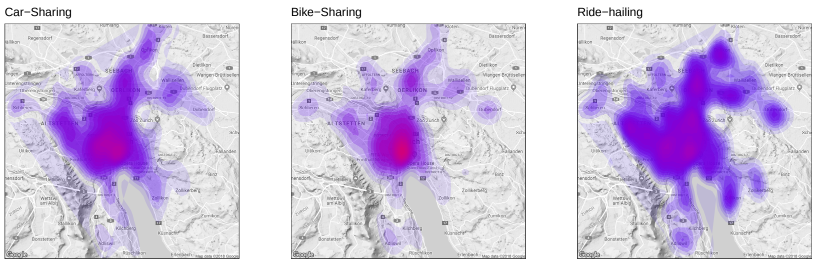
For ride-hailing, operations are profitable for very small fleets of 250 vehicles. For larger fleets, vehicle utilization would not be sufficient to support the high labor costs.



(a) Only one service operating in the area. Fleet size is 250 in each case.



(b) Each service simultaneously operating with fleet size 250.



(c) Each service simultaneously operating with fleet size 4 000 for car- and bike-sharing and 1 000 for ride-hailing.

FIGURE E.3: Rental start locations for selected cases from Scenario 1.

E.5.3 *Impact of full car cost in mode choice*

The results described above all refer to a case, in which shared modes were introduced into today's transport system. Yet, in the current situation, ownership of mobility tools causes a market segmentation into public transport users and car owners (Becker et al., 2017c), leading to sub-optimal mode choice decisions. For private cars, the bias is most substantial, because

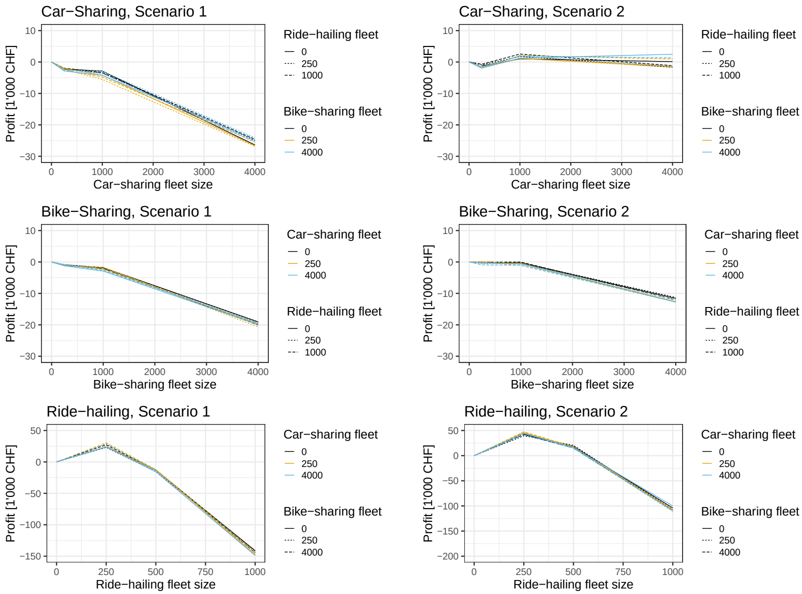


FIGURE E.5: Profit per day for shared modes. Line color and shape denote composition of shared fleet.

agents only consider a part of the full car cost in their mode choice decisions. Therefore, all simulations were repeated in a *Scenario 2*, in which costs for car travel were increased to 0.64 CHF/km), thus including all costs related to car ownership and use.[27]

As shown in Figure E.2, increased costs for car travel lead to a shift of demand towards shared modes. Car-sharing benefits the most with a 25 % surge in the number of rentals. Ride-hailing sees an almost 15 % increase, whereas bike-sharing demand only rises by about 7 %. Also trip distances are getting longer for all shared modes (especially car-sharing and bike-sharing) to replace certain car trips. But despite the higher utilization, access times are only marginally longer.

The increased utilization has substantial impacts on the profitability of car-

27 In this study, fares and subscriptions for public transport operations remain unchanged, because they are set politically and mostly aim at providing a basic level of accessibility for the respective area. Here, a more promising approach would be to prune the network as studied in Section E.5.5.

sharing and bike-sharing. In particular, daily losses for operating a fleet of 1 000 share bikes are reduced to less than 1 CHF per bike. In case of a simultaneous offering of car-sharing and ride-hailing with small fleets, even a profit of up to 0.8 CHF per bike is reached. Yet, most profound impact can be observed for car-sharing. Here, the surge in demand allows for substantial daily profit of up to 3 CHF per vehicle (for fleet size 1 000). The strong increase in profitability for car-sharing can be explained by the high fixed costs (compare Table E.2) of these services. For ride-hailing, a small fleet of up to 500 vehicles can be operated at a daily profit of up to 50 CHF per vehicle, but for larger fleet sizes, the balance turns into a large loss.

E.5.4 *System-level analyses*

Judging from a system's perspective, operator profit is not necessarily the most important target function. Like for public transport, subsidizing such systems may be an interesting option if those schemes contributed to a more efficient transport system or to an increased level of accessibility. To this end, all scenarios were evaluated with respect to their impact on *total travel time*, *total generalized cost* and *total energy consumption*, across all modes.

The results are presented in Figure E.6. The upper plots show the total travel times and provide various key insights: First, introduction of shared modes generally reduces travel times. Hence, despite the slow access walk towards the next available vehicle, they offer a faster alternative than other modes. The effect is especially strong for car-sharing and ride-hailing. Second, transparent car costs (Scenario 2) would increase network travel times, which is the result of a mode shift away from the private car. Indeed, car mode share falls from 49 % to 34 % in the base case (without shared modes). And while the introduction of shared modes helps to reduce total travel time by up to 2 %, increasing perceived car costs drive them up by about 11 %.

Yet, given that different modes provide different levels of comfort, travel times may not be the most important indicator of system performance. As described in Section E.3, a simple welfare measure has been used for this purpose: It includes the disutility of travel for all trips (without fares paid

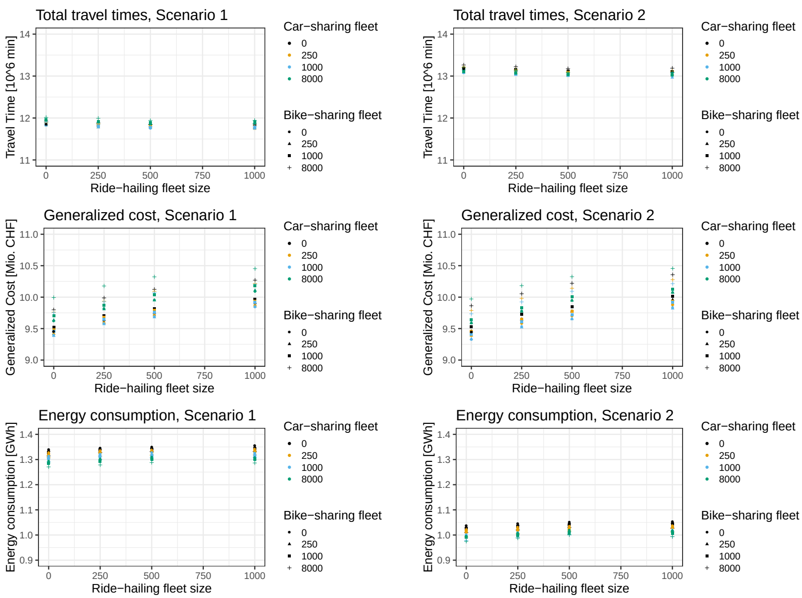


FIGURE E.6: System-level analyses. Color and shape denote composition of shared fleet.

for shared modes) as well as the operating costs of the shared services and subsidies paid for public transport operations. As shown in Figure E.6, the fleet sizes of the three shared modes (and the respective economic losses) are the key drivers of the generalized cost. Interestingly, the base case (zero fleets of shared modes) ranks among the most efficient cases. Hence, the three shared modes do not appear to generate substantial gains in system efficiency. Generalized system cost are slightly lower in *Scenario 2*, which is due to the more efficient mode choice behaviour (hidden car costs are included in the value for *Scneario 1*).

For *Scenario 1*, a fleet of 1 000 car-sharing vehicles, 250 shared bikes and zero ride-hailing activity was found to provide lowest generalized system cost. Yet, savings are not substantial: compared to the baseline case, the potential efficiency gain is less than 1 %. In turn, a case of 1 000 car-sharing vehicles, 1 000 shared bikes and 500 ride-hailing vehicles would generate a 3 % increase in total system cost. In *Scenario 2* (transparent car costs), system-optimum ist shifted towards a fleet of 1 000 free-floating car-sharing vehicles (no other shared modes), and although potential efficiency gains due to introduction of shared modes generally appear higher, savings compared to the respective baseline are still minor.

As a third measure, the impact on total energy consumption was analyzed. Here, all trips with car, car-sharing, ride-hailing and electric bicycles were considered. For public transport the total energy consumption reported by the local tram and bus operator was used.[28] As expected, larger car-sharing and bike-sharing fleets reduce overall energy consumption by up to 7 %, indicating that they do attract substantial demand from other motorized modes (also compare E.7). The most striking difference is between *Scenario 1* and *Scenario 2*: Making agents consider their full car cost would already help to reduce transport-related energy consumption by almost 25 % (for trips within the service area). Concerning the different shared modes, it becomes obvious that only ride-hailing has a slightly negative impact on energy consumption. The reason for this is that it also competes with public transport and active modes, which it cannot make up for by a higher fuel efficiency.[29]

It is important to note that this analysis does not consider any grey energy or impacts on car-ownership, which were found to be the key drivers of the environmental impact of shared modes in earlier research (Shaheen and Cohen, 2013).

E.5.5 *Public Transport Integration*

In Zurich, operations of various bus and tram lines are subsidized, to provide all parts of the city with a dense network of frequent public transport services. For the city alone, subsidies amount to more than 105 Mio. CHF per year.[30] Since shared modes can also be considered as part of public transport services, it is studied to what extent they could substitute highly subsidized bus and tram lines in providing accessibility towards lower-density areas. To this end, all 25 bus and tram lines with a fare recov-

28 129 GWh in 2017 according to VBZ business report: https://www.stadt-zuerich.ch/vbz/de/index/die_vbz/geschaeftsbericht.html

29 For ride-hailing vehicles, the same average fuel consumption as for private cars was assumed.

30 Values are for 2013 and were published by the city's governing council in 2016: https://www.kantonsrat.zh.ch/Dokumente/Df49fc539-2ea1-4654-98df-68d694fec079/R15301.pdf

ery rate of less than 75 % were dropped in return for subsidized offers of shared mobility (see Section E.3 for details). To limit computation time, only a selected number of cases was simulated for this analysis.

Obviously, the subsidies increase attractiveness of shared modes. As a result, the number of ride-hailing trips skyrockets by 55 %. Also, there are 22 % more rentals of car-sharing vehicles and a 9 % increase in bike-sharing use. As a result, ride-hailing becomes highly profitable in all cases (below 1 000 vehicles) and car-sharing is profitable for a fleet size of 1 000 vehicles. Bike-sharing generates a small profit only in *Scenario 2*. These results reflect the amount of subsidies for the different shared modes as presented in Tables E.4 and E.5: By far the most subsidies are paid for ride-hailing trips, whereas car-sharing and bike-sharing rides only attract a marginal share. Most importantly, in all cases the total amount of subsidies is lower than the amount currently paid for regular public transport services on the lines that were dropped (218 400 CHF per day).

In most cases, this monetary gain comes at the expense of slightly increased total travel times. However, the net impact appears to be only marginal: As shown in Tables E.4 and E.5, generalized cost is up to 2 % lower compared to the corresponding case with the full public transport network. Compared to the base case (no shared mobility, full PT network), generalized cost can be slightly reduced by a small car-sharing fleet, but would be 3 % higher for a fleet of 1 000 shared cars, 1 000 shared bikes and 500 ride-hailing vehicles.

In contrast, the impact on energy consumption is substantial with a potential reduction of up to 18 % when dropping the selected bus and tram lines and replacing them with shared modes.[31] Compared to the base case, up to 36 % reduction in total energy consumption is possible through a combination of both the substitution of underused bus lines and the introduction of transparent car costs.

31 Disaggregated data on energy consumption per bus line was not available. Therefore, the total energy consumption for public transport was reduced by 51.5 %, which corresponds to the share of the operating costs of the dropped lines among the total operating cost of all lines.

Fleet size			Travel time [1 000 h]		Gen. cost [Mio. CHF]		Energy [GWh]		Subsidies [kCHF]
CS	BS	RH	base	subst.	base	subst.	base	subst.	CS+BS+RH
0	0	0	198	198	9.45	9.45	1.34	1.34	0.00
250	0	0	197	199	9.41	9.34	1.33	1.18	0.69
0	250	0	197	199	9.46	9.40	1.34	1.19	0.23
0	0	250	197	198	9.63	9.53	1.35	1.21	28.63
250	250	250	196	197	9.59	9.47	1.33	1.19	29.04
1000	1000	500	196	197	9.76	9.56	1.32	1.17	45.06
4000	4000	1000	198	199	10.22	10.01	1.29	1.15	69.13

TABLE E.4: System-level analysis for base case and substitution case, where shared modes are subsidized to replace line-based public transport in certain areas. All numbers are for *Scenario 1*, i.e. mode choice depending on perceived car cost.

Fleet size			Travel time [1 000 h]		Gen. cost [Mio. CHF]		Energy [GWh]		Subsidies [kCHF]
CS	BS	RH	base	subst.	base	subst.	base	subst.	CS+BS+RH
0	0	0	220	220	9.45	9.45	1.04	1.04	0.00
250	0	0	219	220	9.39	9.31	1.02	0.89	0.90
0	250	0	220	221	9.46	9.40	1.03	0.90	0.51
0	0	250	219	220	9.65	9.54	1.05	0.92	36.95
250	250	250	218	219	9.60	9.45	1.03	0.89	34.74
1000	1000	500	217	218	9.72	9.52	1.01	0.87	57.12
4000	4000	1000	218	217	10.21	9.96	0.99	0.86	81.40

TABLE E.5: System-level analysis for base case and substitution case, where shared modes are subsidized to replace line-based public transport in certain areas. All numbers are for *Scenario 2*, i.e. mode choice depending on full car cost.

E.6 DISCUSSION

The simulation results provide various first insights on how *Mobility as a Service* (MaaS) and shared modes can help to increase efficiency of the transport system.

The paper presents a first joint simulation of three types of shared mobility: free-floating car-sharing, free-floating electric bike-sharing and ride-hailing. Although such schemes already co-exist in many cities around the globe, their interaction has rarely been studied yet. The simulation results show that for each of the shared modes, a critical fleet size is required to allow efficient operations. However, once a certain fleet size is reached, demand saturates. Hence, extremely large fleets of shared modes do not appear economical (compare Ciari and Becker (2017)). In addition, the results suggest that there is a twofold interaction between car-sharing and bike-sharing (and to a lesser extent ride-hailing): On the one hand, larger fleets of other shared modes result in competition on the level of single trips. However, since agents plan their whole trip chain in advance, availability of, say, bike-sharing may guarantee a return trip, and thus enable a traveler to use car-sharing for the outbound trip. In fact, such behaviour has earlier been observed for car-pooling, where one of the deterrents is passengers' fear of getting stuck at their destination.

Moreover, the distributions of rental start locations suggest that car-sharing and bike-sharing compete in similar demand hot spots: both serve mostly the densest parts of the city, although demand for car-sharing reaches a bit further out (and generally includes longer trips). But also because of specific characteristics not modeled here (e.g. bicycles consume less space, but car-sharing vehicles are weather-prone and allow transport of larger goods (Becker et al., 2017a)), they should be seen as complements as long as barriers to use both schemes are not too large. In contrast, ride-hailing serves a different demand segment by connecting the outskirts of the city. However, some demand for trips starting within the city center is taken away by car-sharing or bike-sharing.

Yet, the results indicate that on a system level, overall travel time savings induced by shared modes are only marginal and often come at a slight increase in total generalized cost. Capturing all monetary cost and disutility of travel, the generalized cost value can be considered a measure of efficiency of the transport system. Introduction of small fleets of free-floating car-sharing can increase system efficiency by about 1 %, whereas larger fleets and combinations of shared modes appear slightly detrimental. This means that on a system-level operating cost of such services often outweigh the travel time gains they produce. The picture may, however, look different if agents had non-uniform values of time.

Although their impact on system-wide operational efficiency may be limited, car-sharing and bike-sharing were found to have a major impact on energy consumption. In the light of earlier research on bike-sharing (Fishman et al., 2014a), this means that to a substantial degree, both shared modes substitute private car trips. It also supports an earlier study showing that free-floating car-sharing is mostly used for tangential trips and trips for which public transport service is poor (Becker et al., 2017b). Indeed, mode shift findings of this research are compatible with both interpretations. Only for ride-hailing no positive impact on system-wide energy consumption could be found. In fact, energy impacts across all three shared modes should be even higher given that car-ownership reductions (not modelled here) were found earlier to trigger even stronger behavioural change (Shaheen and Cohen, 2013).

Interestingly, in most energy-optimal scenarios, car-sharing and bike-sharing operators operate at substantial losses. In contrast, ride-hailing services may be profitable at limited fleet sizes, but do not generate positive externalities with respect to energy consumption. This raises the political question, whether operators of such systems should be subsidized and/or charged as an incentive to adjust their fleet sizes towards an energy-optimal state.

Moreover, simulation results indicate that shared modes can be an efficient solution to substitute under-used bus services. Since pruning of the network was done in a very rough manner, the actual efficiency gains of complementing a reduced line-based public transport network with subsidized modes of shared mobility may be higher. This insight will also be highly relevant to design public transport networks in an era of automated taxis, which can be operated at even lower cost (Bösch et al., 2018).

Finally, the simulation results confirm the key expectation of *Mobility as a Service* (MaaS), i.e. that an integrated transport system with cost transparency at the trip level helps to increase system efficiency. To study this effect, all simulations in this paper were conducted twice: In *Scenario 1*, car-owners had a private car available for all trips at the generally perceived marginal cost (0.27 CHF/km). In *Scenario 2*, the cost attribute was increased to 0.64 CHF/km, which captures the true cost of the trip (i.e. fixed/sunk cost were converted into marginal cost): This change alone triggered a 25 % reduction in transport-related energy consumption, because many travellers prefered other modes rather than paying the higher price for using a car. Yet, due to longer travel times of the alternative modes, generalized cost are only marginally lower for the case of transparent car prices.

A next step would be to include externalities in the generalized cost, such as grey energy, GHG emissions, noise pollution or space consumption[32]. Moreover, a dedicated mode choice model based on empirical data would be required to obtain even more realistic results. In addition, sensitivity analysis would allow to show how robust the results are for deviations or changes in actual travel behavior. Also, the limited number of cases studied in this research does not allow to identify the optimal combination of different fleet sizes of shared modes, suggesting that the possible impacts may even be higher than reported here. Moreover, the current mode choice approach does not allow inter-modal trips (e.g. using car-sharing as a feeder for public transport). Given the relatively small service area, this limitation will only lead to a small underestimation of demand for shared modes here, but needs to be addressed if larger areas were to be studied.

E.7 CONCLUSION

A key component of *Mobility as a Service* (MaaS) is to allow travellers unbiased choice of modes for each trip. First field tests of MaaS schemes confirmed that in such a setup, test persons do make better choices, both saving money and reducing carbon emissions (Sochor et al., 2016). The results of this research further support this notion by showing that simply by basing mode choice decisions on the full cost of private car travel, transport-related energy consumption can be reduced by 25 %.

32 Space consumption is only indirectly covered by parking cost included in the cost for car and car-sharing.

Moreover, results show that MaaS impacts are even stronger when fleets of shared modes are introduced into the network. In fact, integration of shared modes may even allow efficiency gains on the supply side, when used to provide accessibility to areas, in which demand is too low to support line-based public transportation. Combined with unbiased mode choice decisions, system efficiency can be increased by 2 %, but total energy consumption reduced by another 18 % if shared modes were used to substitute underused bus lines.

It is important to note that in most cases, where shared modes reduce system-level energy consumption, operation of such fleets is unprofitable. Hence, operators may get stuck in a local optimum with small, but potentially profitable fleets. However, only if their operations were subsidized (and simultaneously regulated), their highest system-level impacts could be achieved. In a way, this is similar to the economics of public transportation.

Given the limited number of scenarios this research can only provide first insights into the impacts of large-scale integrated MaaS systems. For example, the large intervals between the studied fleet sizes do not allow to precisely determine the services' actual impacts. Moreover, this study had to rely on partial models for mode choice, which may lead to (minor) bias in agents' behaviour. Hence, the analysis should be validated once comprehensive mode choice models become available. However, already now, the results of this scenario-based analysis may inspire further research to investigate certain aspects in more detail.

Independent of possible uncertainties in the results, it is still unclear how the lessons learned can be put into practise. Difficult issues have to be addressed both at the demand and at the supply side. From a planning perspective, a new definition of public transportation is needed to include certain shared modes. Among other aspects, a measureable minimum level of service will have to be imposed if shared modes were to take over the role of public transportation in certain areas (Hensher, 2017). Finally, more effective measures of taxation (or road pricing) will have to be developed to manage demand towards a more system-optimal state.

APPENDIX

Bike-Sharing Module

Free-floating bike-sharing service for this study is implemented in a similar manner as the free-floating car-sharing service Balac et al. (2019). The fleet of bicycles is available for rental in the service area defined by a shapefile. Upon departure from an activity, agents reserve the closest available bike, which thus becomes unavailable to other customers. The agent is then routed on the shortest path in the road network with a constant speed of 14 km/h.[33] After finishing the bike-sharing trip, the agent leaves the bike at the destination facility, where the bike becomes available to other customers.

An important limitation of the current framework is that it does not consider re-charging of the electric bicycles. In the current bike-sharing scheme in Zurich, this is addressed by both providing customers with bonuses if ending their trip at a charging station and by collecting bicycles with empty batteries to re-charge them. Optimizing this process would require substantial further work, which is out of the scope of this research. For the results presented here, this limitation means that there is a slight underestimation in operating costs and a marginal overestimation in demand.

Information on all rentals is gathered throughout the mobility simulation and stored in the output directory for analyses. Recorded information includes access time, trip duration, bike used, origin coordinate and destination coordinate. Information on bicycle availability and access times is also recorded in 15 min time bins for km^2 zones during the simulation. In the subsequent iteration, to inform mode-choice decision in the subsequent iteration.

Mode Share Impact

The environmental impact of shared modes depends on the conventional modes it substitutes (among other factors). However, switch towards shared modes may also induce second-order impacts. Therefore, Table E.6 summarizes the global change in distance travelled by conventional modes. For

33 This corresponds to average speeds observed at the local electric bike-sharing scheme *Smide* in Zurich.

simplicity, only scenarios with a single shared mode with a fleet size of 1 000 vehicles are considered. Other fleet sizes or combinations of services have been neglected.

The results clearly indicate that all three shared modes have a strong tendency to replace car trips and even more so in case of transparent car costs (*Scenario 2*). Interestingly, use of public transport increases in select cases for bike-sharing and car-sharing fleets. This indicates that such schemes may have a leverage effect: The shared mode may only substitute one leg in a car tour, with the other legs being shifted towards public tranport.

Note that the distance travelled with the shared modes is mostly lower than its combined impact on other modes. Besides more efficient routes, this is due to the fact that access walk to the vehicle was not included in the totals. Anyway, the results have to be treated with caution given that multiple independent simulation runs would be required for each scenario to determine their statistical significance.

ACKNOWLEDGEMENTS

This research was part of a Swiss National Fund project (National Research Program 71: Managing Energy Consumption, project number 407140_153807).

	shared mode	bike	car	public transport	walk
Scen. 1	car-sharing (+38 419 km)	-4 037 km (2.3 %)	-64 645 km (4.1 %)	+2201 km (0.2 %)	-460 km (0.2 %)
	bike-sharing (+14 039 km)	-396 km (0.2 %)	-15 819 km (1.0 %)	-1 025 km (0.1 %)	-1 346 km (0.6 %)
	ride-hailing (+52 349 km)	-6 236 km (3.5 %)	-26 027 km (1.7 %)	-6 964 km (0.6 %)	-6 659 km (3.2 %)
Scen. 2	car-sharing (+51 574 km)	-5 544 km (2.8 %)	-89 883 km (8.3 %)	-6 192 km (0.4 %)	-1 120 km (0.5 %)
	bike-sharing (+16 296 km)	-1 077 km (0.5 %)	-19 240 km (1.8 %)	+1 994 km (0.1 %)	-1 463 km (0.6 %)
	ride-hailing (+66 075 km)	-8 540 km (4.3 %)	-40 163 km (3.7 %)	-4 149 km (0.2 %)	-5 548 km (2.3 %)

TABLE E.6: Changes in total distance travelled by conventional modes induced by appearance of shared modes (example of fleet size of 1 000 vehicles; no mixed occurence of different shared modes is considered).

BIBLIOGRAPHY

6t (2014) One-way carsharing: which alternative to private cars?, *Technical Report*, Paris.

Adnan, M., F. C. Pereira, C. M. L. Azevedo, K. Basak, M. Lovric, S. Raveau Feliu, Y. Zhu, J. Ferreira, C. Zegras and M. E. Ben-Akiva (2015) SimMobility: A Multi-Scale Integrated Agent-based Simulation Platform, paper presented at the *95th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Ambrosino, G., J. D. Nelson, M. Boero and I. Pettinelli (2016) Enabling intermodal urban transport through complementary services: From Flexible Mobility Services to the Shared Use Mobility Agency, *Research in Transportation Economics*, **59**, 179–184.

Andrés, J. and G. Gélvez (2014) Joint Disaggregate Modeling of Car and Motorcycle Ownership: A Case Study of Bogotá, Colombia, *Transportation Research Record*, **2451**, 149–156.

Anowar, S., N. Eluru and L. F. Miranda-Moreno (2014) A Transnational Alternative Modeling Approaches Used for Examining Automobile Ownership: A Comprehensive Review, *Transport Reviews*, **34** (4) 441–473.

Anselin, L. (2009) Spatial regression, in A. S. Fotheringham and P. A. Rogerson (eds.) *SAGE handbook of spatial analysis*, 255–275, SAGE, Los Angeles.

Anselin, L., A. K. Bera, R. Florax and M. J. Yoon (1996) Simple diagnostic tests for spatial dependence, *Regional Science and Urban Economics*, **26**, 77–104.

Armoogrum, J. and J.-L. Madre (1996) Non-Response Correction in the 1993 - 1994 NPTS: The example of daily trips, paper presented at the *4th International Conference on Survey Methods in Transport*, Oxford.

Axhausen, K. W., T. Bischof, R. Fuhrer, R. Neuenschwander, G. Sarlas and P. Walker (2015a) Gesamtwirtschaftliche Effekte des öffentlichen Verkehrs mit besonderer Berücksichtigung der Verdichtungs- und Agglomerationseffekte, Schlussbericht, *Arbeitsberichte Verkehrs- und Raumplanung*, **1079**, IVT, ETH Zurich, Zurich.

Axhausen, K. W., P. Fröhlich and M. Tschopp (2011) Changes in Swiss accessibility since 1850, *Research in Transportation Economics*, **31**, 72–80.

Axhausen, K. W. and T. Gärling (1992) Activity-based approaches to travel analysis: conceptual frameworks, models, and research problems, *Transport Reviews*, **12**, 323–341.

Axhausen, K. W., B. Schmid and C. Weis (2015b) Predicting response rates updated, *Technical Report*, **1063**.

Bachand-Marleau, J., B. H. Y. Lee and A. M. El-Geneidy (2012) Better understanding of factors influencing likelihood o fusing shared bicycle systems and frequency of use, *Transportation Research Record*, **2341**, 66–71.

Balac, M., H. Becker, F. Ciari and K. W. Axhausen (2019) Modeling competing free-floating carsharing operators – A case study for Zurich, Switzerland, *Transportation Research Part C*, **98**, 101–117.

Balac, M., F. Ciari and K. W. Axhausen (2015) Carsharing demand estimation: Zurich, Switzerland, area case study, *Transportation Research Record*, (2536) 10–18.

Balac, M., F. Ciari and K. W. Axhausen (2017) Modeling the impact of parking price policy on free-floating carsharing: Case study for Zurich, Switzerland, *Transportation Research Part C*, **77**, 207–225.

Balac, M., M. Janzen and K. W. Axhausen (2018) Alternative approach to scoring in MATSim and how it affectsactivity rescheduling, paper presented at the *97th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Banister, D. (2002) *Transport Planning*, 2nd edn. edn., Spoon Press, London.

Bau- und Verkehrsdepartement des Kantons Basel-Stadt (2016) Gesamtverkehrsmodell, URL `http://www.mobilitaet.bs.ch/ueber-uns/erhebungen-modelle/gesamtverkehrsmodell.html`.

BBC (2014) Car-sharing scheme car2go to withdraw from the UK, news website, URL `http://www.bbc.com/news/uk-england-birmingham-27546644`.

Becker, H. and K. W. Axhausen (2018) Analyse des Angebots von Catch a Car in Basel, *Arbeitsberichte Verkehrs- und Raumplanung*, **1380**, IVT, ETH Zurich, Zurich.

Becker, H., M. Balac, F. Ciari and K. W. Axhausen (2019) Assessing the welfare impacts of MaaS: A case study in Switzerland, *Transportation Research Part A*. DOI: 10.1016/j.tra.2019.09.027.

Becker, H., F. Ciari and K. W. Axhausen (2017a) Comparing car-sharing schemes in Switzerland: User groups and usage patterns, *Transportation Research Part A*, **97**, 17–29.

Becker, H., F. Ciari and K. W. Axhausen (2017b) Modelling free-floating car-sharing use in Switzerland: A spatial regression and conditional logit approach, *Transportation Research Part C*, **81**, 286–299.

Becker, H., F. Ciari and K. W. Axhausen (2018) Measuring the car ownership impact of free-floating car-sharing - A case study in Basel, Switzerland, *Transportation Research Part D*, **65**, 51–62.

Becker, H., A. Loder, B. Schmid and K. W. Axhausen (2017c) Modeling car-sharing membership as a mobility tool: A multivariate Probit approach with latent variables, *Travel Behaviour and Society*, **8**, 26–36.

Bell, A., M. Fairbrother and K. Jones (2018) Fixed and random effects models: making an informed choice, *Quality & Quantity*, 1–24.

Ben-Akiva, M., M. Bradley, T. Morikawa, J. Benjamin, T. Novak, H. Oppewal and V. Rao (1994) Combining revealed and stated preferences data, *Marketing Letters*, **5**, 335–349.

Ben-Akiva, M. and S. Lerman (1985) *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Cambridge.

Ben-Akiva, M., D. McFadden, K. Train, J. Walker, C. Bhat, M. Bierlaire, D. Bolduc, A. Boersch-Supan, D. Brownstone, D. S. Bunch, A. Daly, A. de Palma, D. Gopinath, A. Karlstrom and M. A. Munizaga (2002) Hybrid Choice Models: Progress and Challenges, *Marketing Letters*, **13**, 163–175.

Bhat, C. R. (2005) A multiple discrete–continuous extreme value model: formulation and application to discretionary time-use decisions, *Transportation Research Part B*, **39** (8) 679–707.

Bhat, C. R., S. Astroza, R. Sidharthan, M. J. B. Alam and W. H. Khushefati (2014) A joint count-continuous model of travel behavior with selection based on a multinomial probit residential density choice model, *Transportation Research Part B*, **68**, 31–51.

Bhat, C. R., A. R. Pinjari, S. K. Dubey and A. S. Hamdi (2016) On accommodating spatial interactions in a Generalized Heterogeneous Data Model (GHDM) of mixed types of dependent variables, *Transportation Research Part B*, **94**, 240–263.

Bhat, C. R. and S. Sen (2006) Household vehicle type holdings and usage: an application of the multiple discrete-continuous extreme value (MDCEV) model, *Transportation Research Part B*, **40** (1) 35–53.

BMW AG, DLR, DB Rent GmbH, Landeshauptstadt München, Universität der Bundeswehr München and Senatsverwaltung für Stadtentwicklung und Umwelt Berlin (2016) Wirkung von E-Car Sharing Systemen auf Mobilität und Umwelt in urbanen Räumen (WiMobil), *Technical Report*.

Bolduc, D. and R. Alvarez-Daziano (2010) On estimation of hybrid choice models, *Choice Modelling: The State-of-the-Art and the State-of-Practice, Proceedings from the Inaugural International Choice Modelling Conference*, 259–287.

Bollen, K. A. (1989) *Structural Equations With Latent Variables*, John Wiley & Sons, New York.

Bongart, D. and G. Wilke (2008) Innovation and diffusion of car-sharing for sustainable consumption and production of urban mobility, paper presented at the *2nd Conference of the Sustainable Consumption Research Exchange (SCORE!) Network*, 61–66, Brussels.

Bösch, P., F. Becker, H. Becker and K. W. Axhausen (2018) Cost-based Analysis of Autonomous Mobility Services, *Transport Policy*, **64**, 76–29.

Brandstätter, G., M. Kahr and M. Leitner (2017) Determining optimal locations for charging stations of electric car-sharing systems under stochastic demand, *Transportation Research Part B*, **104**, 17–35.

Bricka, S. and C. R. Bhat (2006) A comparative analysis of GPS-based and travel survey-based data, *Transportation Research Record*, **1972**, 9–20.

Bryson, A., L. Cappellari and C. Lucifora (2004) Does union membership really reduce job satisfaction?, *British Journal of Industrial Relations*, **42** (3) 439–459.

Buck, D., R. Buehler, P. Happ, B. Rawls, P. Chung and N. Borecki (2013) Are bikeshare users different from regular cyclists?, *Transportation Research Record*, **2387**, 112–119.

Buehler, R. (2011) Determinants of transport mode choice: a comparison of Germany and the USA, *Journal of Transport Geography*, **19**, 644–657.

Bundesamt für Raumentwicklung (2017) Verkehrserschliessung in der Schweiz, Webpage (last accessed 14.02.2017), URL `https://www.are.admin.ch/are/de/home/verkehr-und-infrastruktur/grundlagen-und-daten/verkehrserschliessung-in-der-schweiz.html`.

Burkhardt, J. and A. Millard-Ball (2006) Who Is Attracted to Carsharing?, *Transportation Research Record*, **1986**, 98–105.

Cameron, A. C. and K. Trivedi, Pravin (2015) Count Panel Data, in B. H. Baltagi (ed.) *The Oxford Handbook of Panel Data*, chap. 8, Oxford University Press, Oxford.

Cameron, A. C. and P. K. Trivedi (2004) *Microeconomics: Methods and Applications*, Cambridge University Press, Cambridge.

Cameron, A. C. and P. K. Trivedi (2009) *Microeconometrics using Stata*, Stata Press, College Station.

Cameron, C. and P. Trivedi (1990) Regression-based tests for overdispersion in the Poisson model, *Journal of Econometrics*, **46**, 347–364.

Cao, X., P. L. Mokhtarian and S. L. Handy (2009) Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings, *Transport Reviews*, **29** (3) 359–395.

Cappellari, L. and S. P. Jenkins (2006) Calculation of multivariate normal probabilities by simulation, with applications to maximum simulated likelihood estimation, *Stata Journal*, **6** (2) 156–189.

Carrasco, R. (2001) Binary Choice With Binary Endogenous Regressors in Panel Data, *Journal of Business & Economic Statistics*, **19** (4) 385–394.

Celsor, C. and A. Millard-Ball (2007) Where Does Carsharing Work?: Using Geographic Information Systems to Assess Market Potential, *Transportation Research Record*, **1992**, 61–69.

Cervero, R. (2002) Built environment and mode choice: toward a normative framework, *Transportation Research Part D*, **7**, 265–284.

Cervero, R. (2017) Mobility Niches: Jitneys to Robo-Taxis, *Journal of the American Planning Association*, **83**, 404–412.

Cervero, R., A. Golub and B. Nee (2007) City CarShare: Longer-Term Travel Demand and Car Ownership Impacts, *Transportation Research Record*, **1992**, 70–80.

Cervero, R. and Y. Tsai (2004) City CarShare in San Francisco, California: Second-Year Travel Demand and Car Ownership Impacts, *Transportation Research Record*, **1887**, 117–127.

Chambers, J. M. (1992) Linear models, in J. M. Chambers and T. J. Hastie (eds.) *Statistical Models in S*, chap. 4, Wadsworth & Brooks/Cole, Pacific Grove.

Chen, T. D. and K. M. Kockelman (2016) Carsharing's Life-Cycle Impacts on Energy Use and Greenhouse Gas Emission, *Transportation Research Part D*, **47**, 276–284.

Cherlow, J. R. (1981) Measuring Values of Travel Time Savings, *Journal of Consumer Research*, **7**, 360–371.

Chorus, C. G., T. A. Arentze and H. J. Timmermans (2008) A Random Regret-Minimization model of travel choice, *Transportation Research Part B*, **42**, 1–18.

Chorus, C. G. and M. Kroesen (2014) On the (im-)possibility of deriving transport policy implications from hybrid choice models, *Transport Policy*, **36**, 217–222.

Ciari, F. and K. W. Axhausen (2012) Choosing carpooling or carsharing as a mode: Swiss stated choice experiments, paper presented at the *91st Annual Meeting of the Transportation Research Board*, Washington, D.C.

Ciari, F., M. Balac and K. W. Axhausen (2016) Modeling Carsharing with the Agent-Based Simulation MATSim: State of the Art, Applications, and Future Developments, *Transportation Research Record*, **2564**, 14–20.

Ciari, F., M. Balac and M. Balmer (2015a) Modeling the effect of different pricing schemes on free-floating carsharing travel demand: a test case for Zurich, *Transportation*, **42**, 413–433.

Ciari, F. and H. Becker (2017) How disruptive can shared mobility be? A scenario-based evaluation of shared mobility systems implemented at large scale, *Disrupting Mobility*, 51–63.

Ciari, F., B. Bock and M. Balmer (2014) Modeling Station-Based and Free-Floating Carsharing Demand, *Transportation Research Record*, **2416**, 37–47.

Ciari, F., N. Schüssler and K. W. Axhausen (2013) Estimation of carsharing demand using an activity-based microsimulation approach: model discussion and some results, *International Journal of Sustainable Transportation*, **7**, 70–84.

Ciari, F., C. Weis and M. Balac (2015b) Evaluating the influence of carsharing stations' location on potential membership: a Swiss case study, *EURO Journal on Transportation and Logistics*, 1–25.

Cliff, A. D. and J. K. Ord (1973) *Spatial processes: models & applications*, Pion, London.

Cottrill, C. D., F. C. Pereira, F. Zhao, I. F. Dias, H. B. Lim, M. E. Ben-Akiva and P. C. Zegras (2013) The Future Mobility Survey: Experiences in developing a smartphone-based travel survey in Singapore, *Transportation Research Record*, **2354**, 59–67.

Cudahy, B. J. (1995) *Under the Sidewalks of New York: The Story of the Greatest Subway System in the World*, Fordham University Press, New York.

Dal, U., T. Erdogan, B. Resitoglu and H. Baydagi (2009) Determination of preferred walking speed on treadmill may lead to high oxygen cost on treadmill walking, *Gait & Posture*, **31** (3) 366–369.

Daly, A. (1987) Estimating tree logit models, *Transportation Research Part B*, **21**, 251–267.

Daly, A., S. Hess, B. Patruni, D. Potoglou and C. Rohr (2012) Using ordered attitudinal indicators in a latent variable choice model: A study of the impact of security on rail travel behaviour, *Transportation*, **39** (2) 267–297.

Day, J. R. and J. Reed (1963) *The Story of London's Underground*, Capital Transport, Berkshire.

de Jong, G., J. Fox, A. Daly, M. Pieters and R. Smit (2004) A comparison of car ownership models, *Transport Reviews*, **24** (4) 379–408.

De Jong, G. C. (1990) An indirect utility model of car ownership and private car use, *European Economic Review*, **34**, 971–985.

de Jong, G. C. and R. Kitamura (2009) A review of household dynamic vehicle ownership models: Holdings models versus transactions models, *Transportation*, **36** (6) 733–743.

de Lorimier, A. and A. M. El-Geneidy (2013) Understanding the Factors Affecting Vehicle Usage and Availability in Carsharing Networks: A Case Study of Communauto Carsharing System from Montréal, Canada, *International Journal of Sustainable Transportation*, **7** (1) 35–51.

Deadman, D. and Z. MacDonald (2004) Offenders as Victims of Crime? An Investigation into the Relationship between Criminal Behaviour and Victimization, *Journal of the Royal Statistical Society, Series A*, **167** (1) 53–67.

Deng, Y. and M.-A. Cardin (2018) Integrating operational decisions into the planning of one-way vehicle-sharing systems under uncertainty, *Transportation Research Part C*, **86**, 407–424.

Dias, F. F., P. Lavieri, V. M. Garikapati, S. Astroza, R. M. Pendyala and C. R. Bhat (2017) A Behavioral Choice Model for the Use of Car-Sharing and Ride-Sourcing Services, paper presented at the *96th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Djavadian, S. and J. Y. J. Chow (2017) An agent-based day-to-day adjustment process for modeling Mobility as a Service with a two-sided flexible transport market, *Transportation Research Part B*, **104**, 36–57.

Dobler, C. and G. Lämmel (2016) The Multi-Modal Contribution, in A. Horni, K. Nagel and K. W. Axhausen (eds.) *The Multi-Agend Transport Simulation MATSim*, 135–140, Ubiquity Press, London.

Dobson, R., F. Dunbar, C. J. Smith, D. Reibstein and C. Lovelock (1978) Structural models for the analysis of traveler attitude-behavior relationships, *Transportation*, **7** (4) 351–363.

Dubernet, T. and K. W. Axhausen (2014) A multiagent simulation framework for evaluating bike redistribution systems in bike sharing schemes, *Arbeitsberichte Verkehrs- und Raumplanung*, **1010**, IVT, ETH Zurich, Zurich.

Eiro, T. and L. M. Martinez (2014) Analyzing Impacts of New Shared Transport Alternatives in an Urban Mobility System, paper presented at the *93rd Annual Meeting of the Transportation Research Board*, Washington, D.C.

Eluru, N., C. R. Bhat, R. M. Pendyala and K. C. Konduri (2010) A joint flexible econometric model system of household residential location and vehicle fleet composition/usage choices, *Transportation*, **37**, 603–626.

Ewing, R. and R. Cervero (2010) Travel and the Built Environment, *Journal of the American Planning Association*, **76** (3) 265–294.

Faghih-Imani, A. and N. Eluru (2018) A finite mixture modeling approach to examine New York City bicycle sharing system (CitiBike) users' destination preferences, *Transportation*, 1–25.

Feil, M. (2010) Choosing the daily schedule: Expanding activity-based travel demand modelling, Ph.D. Thesis, ETH Zurich.

Fifer, S., J. Rose and S. Greaves (2014) Hypothetical bias in Stated Choice Experiments: Is it a problem? And if so, how do we deal with it?, *Transportation Research Part A*, **61**, 164–177.

Firnkorn, J. (2012) Triangulation of two methods measuring the impacts of a free-floating carsharing system in Germany, *Transportation Research Part A*, **46** (10) 1654–1672.

Firnkorn, J. and M. Müller (2011) What will be the environmental effects of new free-floating car-sharing systems? The case of car2go in Ulm, *Ecological Economics*, **70** (8) 1519–1528.

Firnkorn, J. and M. Müller (2012) Selling Mobility instead of Cars: New Business Strategies of Automakers and the Impact on Private Vehicle Holding, *Business Strategy and the Environment*, **21** (4) 264–280.

Fishman, E. (2016) Bikeshare: A Review of Recent Literature, *Transport Reviews*, **36**, 92–113.

Fishman, E., S. Washington and N. Haworth (2013) Bike Share: A Synthesis of the Literature, *Transport Reviews*, **33**, 148–165.

Fishman, E., S. Washington and N. Haworth (2014a) Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia, *Transportation Research Part D*, **31**, 13–20.

Fishman, E., S. Washington, N. Haworth and W. A. (2015) Factors influencing bike share membership: An analysis of Melbourne and Brisbane, *Transportation Research Part A*, **71**, 17–30.

Fishman, E., S. Washington, N. Haworth and A. Mazzei (2014b) Barriers to bikesharing: An analysis from Melbourne and Brisbane, *Journal of Transport Geography*, **41**, 325–337.

Fosgerau, M., E. Freijinger and Karlström (2013) A link based network route choice model with unrestricted choice set, *Transportation Research Part B*, **56**, 70–80.

Frei, C., M. Hyland and H. S. Mahmassani (2017) Flexing service schedules: Assessing the potential for demand-adaptive hybrid transit via a stated preference approach, *Transportation Research Part C*, **76**, 71–89.

Giesel, F. and C. Nobis (2016) The Impact of Carsharing on Car Ownership in German Cities, *Transportation Research Procedia*, **19**, 215–224.

Golob, T. F. (2003) Structural equation modeling for travel behavior research, *Transportation Research Part B*, **37** (1) 1–25.

Goodfellow, I., Y. Bengio and A. Courville (2016) *Deep Learning*, MIT Press, Cambridge.

Google (2016) Google Maps APIs, URL `https://developers.google.com/maps/`.

Grasset, V. and C. Morency (2010) Carsharing: Analyzing the Interaction Between Neighborhood Features and Market Share, paper presented at the *89th Annual Meeting of the Transportation Research Board*.

Greene, W. H. (2012) *Econometric analysis*, 7th edn., international edn., Boston, MA: Pearson.

Griffith, D. A. and F. Csillag (1993) Exploring relationships between semivariogram and spatial autoregressive models, *Papers in Regional Science*, **72** (3) 283–295.

Guidon, S., H. Becker, H. Dediu and K. W. Axhausen (2019) Electric bicyclesharing: a new competitor in the urban transportation market?: An empirical analysis of transaction data, *Transportation Research Record*, **2673** (4) 15–26.

Gulati, R. and M. C. Higgins (2003) Which ties matter when? The contingent effects of interorganizational partnerships on IPO success, *Strategic Management Journal*, **24** (2) 127–144.

Gumbel, E. J. (1960) Multivariate Extremal Distributions, *Bulletin of the International Statistical Institute*, **37**, 471–475.

Habibi, S., F. Sprei, C. Englund, S. Pettersson, A. Voronov, J. Wedlin and H. Engdahl (2017) Comparison of free-floating car sharing services in cities.

Hainmueller, J., D. Hangartner and T. Yamamoto (2015) Validating vignette and conjoint survey experiments against real-world behavior, *Proceedings of the National Academies of the Sciences*, **112**, 2395–2400.

Hamilton, J. D. (1994) *Time Series Analysis*, Princeton University Press, Princeton.

Hansen, W. G. (1959) How Accessibility Shapes Land Use, *Journal of the American Institute of Planners*, **25** (2) 73–76.

Harms, S. and B. Truffer (1998) The emergence of a nationwide carsharing co-operative in Switzerland, *Research Report*, EAWAG (Eidgenössische Anstalt für Wasserversorgung, Abwasserreinigung und Gewässerschutz).

Hausman, J. A. and D. L. McFadden (1984) Specification tests for the multinomial logit model, *Econometrica*, **52**, 1219–1240.

Hayton, J. C., D. G. Allen and V. Scarpello (2004) Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis, *Organizational Research Methods*, **7** (2) 191–205.

Hebenstreit, C. and M. Fellendorf (2018) A dynamic bike sharing module for agent-based transport simulation, within multimodal context, *Procedia Computer Science*, **130**, 65–72.

Heckman, J. J. (1974) Shadow Prices, Market Wages, and Labor Supply, *Econometria*, **42** (4) 679–694.

Heckman, J. J. (1976) The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models, *Annals of Economic and Social Measurement*, **5** (4) 475–492.

Heckman, J. J. (1979) Sample Selection Bias as a Specification Error, *Econometria*, **47** (1) 153–161.

Heilig, M., N. Mallig, O. Schröder, M. Kagerbauer and P. Vortisch (2017) Implementation of free-floating and station-based carsharing in an agent-based travel demand model, *Travel Behaviour and Society*.

Henao, A. and W. E. Marshall (2018) The impact of ride-hailing on vehicle miles traveled, *Transportation*, 1–22.

Hensher, D. A. (2017) Future bus transport contracts under a mobility as a service (MaaS) regime in the digital age: Are they likely to change?, *Transportation Research Part A*, **98**, 86–96.

Hensher, D. H. and W. H. Greene (2003) The Mixed Logit model: The state of practice, *Transportation*, **30**, 133–176.

Hess, S., A. Erath and K. W. Axhausen (2008) Estimated Value of Savings in Travel Time in Switzerland, *Transportation Research Record*, **2082**, 43–55.

Hole, A. R. (2007) Fitting mixed logit models by using maximum simulated likelihood, *Stata Journal*, **7**, 388–401.

Hörl, S. (2017) Agent-based simulation of autonomous taxi services with dynamic demand responses, *Procedia Computer Science*, **109**, 899–904.

Hörl, S., M. Balac and K. W. Axhausen (2018a) A first look at bridging discrete choice modeling and agent-based microsimulation in MATSim, *Procedia Computer Science*, **130**, 900–907.

Hörl, S., M. Balac and K. W. Axhausen (2019) Pairing discrete mode choice models and agent-based transport simulation with MATSim, paper presented at the *98th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Hörl, S., F. Becker, T. Dubernet and K. W. Axhausen (2018b) Induzierter Verkehr durch autonome Fahrzeuge: Eine Abschätzung, *Technical Report*, Federal Roads Office, Ittingen.

Horni, A., K. Nagel and K. W. Axhausen (2016) *The Multi-Agent Transport Simulation MATSim*, Ubiquity Press, London.

Jenkins, S. P., L. Cappellari, P. Lynn, A. Jäckle and E. Sala (2006) Patterns of consent: Evidence from a general household survey, *Journal of the Royal Statistical Society, Series A*, **169** (4) 701–722.

Jittrapirom, P., V. Caiati, A.-M. Feneri, S. Ebrahimigharehbaghi, M. J. Alonso-Gonzalez and J. Narayan (2017) Mobility as a Service: A Critical Review of Definitions, Assessments of Schemes, and Key Challenges, *Urban Planning*, **2** (2) 13–25.

Jöreskog, K. G. and A. S. Goldberger (1975) Estimation of a model with multiple indicators and multiple causes of a single latent variable, *Journal of the American Statistical Association*, **70** (351a) 631–639.

Jorge, D., C. Barnhart and G. Correia (2015a) Assessing the viability of enabling a round-trip carsharing system to accept one-way trips: Application to Logan Airport in Boston, *Transportation Research Part C*, **56**, 359–372.

Jorge, D. and G. Correia (2013) Carsharing systems demand estimation and defined operations: a literature review, *European Journal of Transport and Infrastructure Research*, **13** (3) 201–220.

Jorge, D., G. Molnar and G. Correia (2015b) Trip pricing of one-way station-based carsharing networks with zone and time of day price variations, *Transportation Research Part B*, **81**, 461–482.

Juschten, M., T. Ohnmacht, V. T. Thao, R. Gerike and R. Hössinger (2017) Carsharing in Switzerland: identifying new markets by predicting membership based on data on supply and demand, *Transportation*, 1–24.

Kamargianni, M., W. Li, M. Matyas and A. Schäfer (2016) A critical review of new mobility services for urban transport, *Transportation Research Procedia*, **14**, 3294–3303.

Kang, J., K. Hwang and S. Park (2016) Finding factors that influence carsharing usage: Case study in Seoul, *Sustainability*, **8**, 709.

Kelejan, H. H. and I. R. Prucha (1999) A generalized moments estimator for the autoregressive parameter in a spatial model , *International Economic Review*, **40** (2) 509–533.

Kim, M. and P. Schonfeld (2015) Maximizing net benefits for conventional and flexible bus services, *Transportation Research Part A*, **80**, 116–133.

Kopec, J. A. and J. M. Esdaile (1990) Bias in case-control studies. A review, *J Epidemiol Community Health*, **44** (3) 179–186.

Kopp, J., R. Gerike and K. W. Axhausen (2013) Status Quo and Perspectives for CarSharing Systems: the Example of DriveNow, in R. Gerike, F. Hülsmann and K. Roller (eds.) *Strategies for Sustainable Mobilities: Opportunities and Challenges*, 207–226, Ashgate, Burlington.

Kopp, J., R. Gerike and K. W. Axhausen (2015) Do sharing people behave differently? An empirical evaluation of the distinctive mobility patterns of free-floating car-sharing members, *Transportation*, **42** (3) 449–469.

Kortum, K. and R. Machemehl (2012) Free Floating Carsharing Systems: Innovations in Membership Prediction, Mode Share, and Vehicle Allocation Optimization Methodologies, *Technical Report*, **SWUUTC/12/476660-00079-1**, Southwest Region University Transportation Center, Center for Transportation Research, University of Texas at Austin.

Kortum, K., R. Schönduwe, B. Stolte and B. Bock (2016) Free-Floating Carsharing: City-Specific Growth Rates and Success Factors, *Transportation Research Procedia*, **19**, 328–340.

Kowald, M., B. Kieser, N. Mathys and A. Justen (2017) Determinants of mobility resource ownership in Switzerland: changes between 2000 and 2010, *Transportation*, **44**, 1043–1065.

Lambert, D. (1992) Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing, *Technometrics*, **34** (1) 1–14.

Lane, C. (2005) PhillyCarShare - First-year social and mobility impacts of carsharing in Philadelphia, Pennsylvania, *Transportation Research Record*, **1927**, 158–166.

Le Vine, S. (2011) Strategies for personal mobility: A study of consumer acceptance of subscription drive-it-yourself car services, Ph.D. Thesis, Imperial College London.

Le Vine, S., O. Adamou and J. Polak (2014) Predicting new forms of activity/mobility patterns enabled by shared-mobility services through a needs-based stated-response method: Case study of grocery shopping, *Transport Policy*, **32**, 60–68.

Le Vine, S., M. Lee-Gosselin, A. Sivakumar and J. Polak (2011) Design of a Strategic-Tactical Stated-Choice Survey Methodology Using a Constructed Avatar, *Transportation Research Record*, **2246**, 55–63.

Le Vine, S., M. Lee-Gosselin, A. Sivakumar and J. Polak (2014) A new approach to predict the market and impacts of round-trip and point-to-point carsharing systems: Case study of London, *Transportation Research Part D*, **32**, 218–229.

Le Vine, S. and J. Polak (forthcoming) The impact of free-floating carsharing on car ownership: Early-stage findings from London, *Transport Policy*.

Leclerc, B., M. Trépanier and C. Morency (2013) Unraveling the Travel Behavior of Carsharing Members from Global Positioning System Traces, *Transportation Research Record*, **2359**, 59–67.

Li, C. (2013) Little's test of missing completely at random, *The Stata Journal*, **13** (4) 795–809.

Li, Q., F. Liao, H. J. P. Timmermans, H. Huang and J. Zhou (2018) Incorporating free-floating car-sharing into an activity-based dynamic user equilibrium model: A demand-side model, *Transportation Research Part B*, (107) 102–123.

Li, W. and M. Kamargianni (2018) Providing quantified evidence to policy makers for promoting bike-sharing in heavily air-polluted cities: A mode choice model and policy simulation for Taiyuan-China, *Transportation Research Part A*, (111) 277–291.

Li, X. and Quadrifoglio (2010) Feeder transit services: Choosing between fixed and demand responsive policy, *Transportation Research Part C*, **18**, 770–780.

Liang, K.-Y. and S. L. Zeger (1986) Longitudinal data analysis using generalized linear models, *Biometrica*, **73**, 13–22.

Litman, T. (2000) Evaluating Carsharing Benefits, *Transportation Research Record*, **1702** (1) 31–35.

Loder, A., Ambühl, M. Menendez and K. W. Axhuasen (2017) Empirics of multi-modal traffic networks - Using the 3D macroscopic fundamental diagram, *Transportation Research Part C*, **82**, 88–101.

Loder, A. and K. W. Axhausen (2018) Mobility tools and use: Accessibility's role in Switzerland, *Journal of Transport and Land Use*, **11**, 367–385.

Louviere, J. J., D. A. Hensher and J. D. Swait (2000) *Stated Choice Methods: Analysis and Applications*, Cambridge University Press, Cambridge.

Maciejewski, M. (2016) Dynamic Transport Services, in A. Horni, K. Nagel and K. W. Axhausen (eds.) *The Multi-Agend Transport Simulation MATSim*, 145–152, Ubiquity Press, London.

Martin, E. and S. Shaheen (2011a) Greenhouse gas emission impacts of carsharing in North America, *Intelligent Transportation Systems*, **12** (4) 1074–1086.

Martin, E. and S. Shaheen (2011b) The impact of carsharing on public transit and non-motorized travel: An exploration of North American carsharing survey data, *Energies*, **4** (11) 2094–2114.

Martin, E., S. Shaheen and J. Lidicker (2010) Impact of Carsharing on Household Vehicle Holdings, *Transportation Research Record: Journal of the Transportation Research Board*, **2143**, 150–158.

Martin, E. and S. A. Shaheen (2016) Impacts of car2go on Vehicle Ownership, Modal Shift, Vehicle Miles Travelled, and Greenhouse Gas Emissions: An Analysis of Five North American Cities, *Technical Report*, Transportation Sustainability Research Center (TSRC), Berkeley.

Martin, E. W. and S. A. Shaheen (2014) Evaluating public transit modal shift dynamics in response to bikesharing, *Journal of Transport Geography*, **41**, 315–324.

Matyas, M. and K. Kamargianni (2017) Stated Preference Design for Exploring Demand for "Mobility as a Service" Plans, paper presented at the *5th International Choice Modelling Conference*, Cape Town.

McFadden, D. (1974a) The measurment of urban travel demand, *Journal of Public Economics*, **3**, 303–328.

McFadden, D. L. (1974b) Conditional logit analysis of qualitative choice behavior, in P. Zarembka (ed.) *Frontiers in Econometrics*, 105–142, Academic Press, New York.

Meijkamp, R. (1998) Eco-Efficient Services: an Empirical Study of Car Sharing in the Netherlands, *Business Strategy and the environment*, **7**, 234–244.

Meyer de Freitas, L., H. Becker, M. Zimmermann and K. W. Axhausen (2019) Modelling intermodal travel in Switzerland: A recursive logit approach, *Transportation Research Part A*, **119**, 200–213.

Miguel Martinez, L., G. Homem de Almeida Correia, F. Moura and M. Mendes Lopes (2017) Insights into carsharing demand dynamics: Outputs of an agent-based model application to Lisbon, Portugal, *International Journal of Sustainable Transportation*, **11** (2) 148–159.

Millard-Ball, A., G. Murray, J. t. Schure, C. Fox and J. Burkhardt (eds.) (2005) *Car-Sharing: Where and How It Succeeds*, vol. 108 of *Transit Cooperative Research Program Report (TCRP)*, Transportation Research Board, Washington, D.C.

Mishra, G. S., R. R. Clewlow, P. L. Mokhtarian and K. F. Widaman (2015) The effect of carsharing on vehicle holdings and travel behavior: A propensity score and causal mediation analysis of the San Francisco Bay Area, *Research in Transportation Economics*, **52**, 46–55.

Mobility Car-Sharing (2017) Mobility stations, Webpage (last accessed 14.02.2017), URL `https://www.mobility.ch/en/private-customers/mobility-stations/`.

Mokhtarian, P. and W. Tang (2013) Trivariate probit models of pre-purchase/purchase shopping channel choice: clothing purchases in Northern California, in S. Hess and A. Daly (eds.) *Choice Modelling*, chap. 12, 243–273, Edward Elgar, London.

Mokhtarian, P. L. and X. Cao (2008) Examining the Impacts of Residential Self-selection on Travel Behavior: A Focus on Methodologies, *Transportation Research Part B*, **42** (3) 204–228.

Montini, L., N. Rieser-Schüssler and K. W. Axhausen (2013) Field Report: One-Week GPS-based Travel Survey in the Greater Zurich Area, paper presented at the *Swiss Transport Research Conference*, Monte Verita.

Morris, S. (2007) The impact of obesity on employment, *Labour Economics*, **14** (3) 413–433.

Muheim, P. and E. Reinhardt (1999) Carsharing: The key to combined mobility, *The Journal of World Transport Policy & Practice*, **5** (3) 58–71.

Mulley, C. (2017) Mobility as a Service (MaaS) - does it have critical mass?, *Transport Reviews*, **37**, 247–251.

Mulley, C. and J. D. Nelson (2009) Flexible Transport Services: A new market opportunity for public transport, *Research in Transportation Economics*, **25**, 39–45.

Oehlert, G. W. (1992) A note on the delta method, *The American Statistician*, **46** (1) 27–29.

Oliveira, M. G. S., P. Vovsha, J. Wolf, Y. Birotker, D. Givon and J. Paasche (2011) Global Positioning System-Assisted Prompted Recall Household Travel Survey to Support Development of Advanced Travel Model in Jerusalem, Israel, *Transportation Research Record*, **2246**, 16–23.

Ordoñez Medina, S. A. (2017) Scheduling weekly flexible activities in a large-scale multi-agent mobility simulator, paper presented at the *8th International Conference on Antonomous Agents and Multiagent Sytems (AA-MAS 2017)*, São Paulo, May 2017.

Ortuzar, J. d. D. and L. G. Willumsen (1990) *Modeling Transport*, John Wiley & Sons, Chichester.

Owens, S. (1995) From 'predict and provide' to 'predict and prevent'?: Pricing and planning in transport policy, *Transport Policy*, **2**, 43–49.

Paleti, R., C. Bhat and R. Pendyala (2013) Integrated Model of Residential Location, Work Location, Vehicle Ownership, and Commute Tour Characteristics, *Transportation Research Record*, **2382**, 162–172.

Parkes, S. D., G. Marsden, S. A. Shaheen and A. P. Cohen (2013) Understanding the diffusion of public bikesharing systems: Evidence from Europe and North America, *Journal of Transport Geography*, **31**, 94–103.

Perboli, G., F. Ferrero, S. Musso and A. Vesco (2018) Business models and tariff simulation in car-sharing services, *Transportation Research Part A*, **115**, 32–48.

Pinjari, A., N. Eluru, C. Bhat, R. Pendyala and E. Spissu (2008) Joint model of choice of residential neighborhood and bicycle ownership: accounting for self-selection and unobserved heterogeneity, *Transportation Research Record*, **2082**, 17–26.

Piras, G. (2010) sphet: Spatial models with heteroskedastic innovations in R, *Journal of Statistical Software*, **35** (1) 1–21.

Planungsbüro Jud (2012) Städtevergleich Mobilität, *Technical Report*, Basel-Stadt, Stadt Bern, Stadt Luzern, Stadt St.Gallen, Stadt Winterthur and Stadt Zürich (eds.), Kloten.

Potoglou, D. and Y. O. Susilo (2008) A Comparison of Disaggregate Car Ownership Models, *Transportation Research Record*, **6** (2076) 97–105.

Qiu, H., R. Li and J. Zhao (2018) Daily Level Dynamic Pricing in Shared Mobility-on-Demand Service, paper presented at the *97th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Raux, C., A. Zoubir and M. Geyik (2017) Who are bike sharing schemes members and do they travel differently? The case of Lyon's Velo'v scheme, *Transportation Research Part A*, **106**, 350–363.

Raveau, S., R. Alvarez-Daziano, Y. Yanez, D. Bolduc and J. de Dios Ortuzar (2010) Sequential and simultaneous estimation of hybrid discrete choice models: Some new findings, *Transportation Research Record*, **2156**, 131–139.

Raviv, T., M. Tzur and I. A. Forma (2013) Static repositioning in a bike-sharing system: models and solution approaches, *EURO Journal on Transportation and Logistics*, 187–229.

Rayle, L., D. Dai, N. Chan, R. Cervero and S. Shaheen (2016) Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco, *Transport Policy*, **45**, 168–178.

Ricci, M. (2015) Bike sharing: A review of evidence on impacts and processes of implementation and operation, *Research in Transportation Business and Management*, **15**, 28–38.

Rydén, C. and E. Morin (2005) Environmental assessment: Report WP 6, *Technical Report*, Trivector Traffic, Stockholm.

Sanko, N., D. Dissanayake, S. Kurauchi, H. Maesoba, T. Yamamoto and T. Morikawa (2012) Household car and motorcycle ownership in Bangkok and Kuala Lumpur in comparison with Nagoya, *Transportmetrica A*, **10** (3) 187–213.

Schmid, B., S. Schmutz and K. W. Axhausen (2016) Exploring the choice between in-store and online shopping, paper presented at the *23rd EIRASS conference on Recent Advances in Retailing and Service Strategies*, Edinburgh.

Schmöller, S., S. Weikl, J. Müller and K. Bogenberger (2015) Empirical analysis of free-floating carsharing usage: The Munich and Berlin case, *Transportation Research Part C*, **56**, 34–51.

Scott, D. M. and K. W. Axhausen (2006) Household mobility tool ownership: Modeling interactions between cars and season tickets, *Transportation*, **33** (4) 311–328, ISSN 00494488.

Seattle Department of Transportation (2014) 2013 Seattle Free-Floating Car Share Pilot Program Report, *Technical Report*, Seattle Department of Transportation, Seattle.

Seign, R., M. Schüssler and K. Bogenberger (2015) Enabling sustainable transportation: The model-based determination of business/operating areas of free-floating carsharing systems, *Research in Transportation Economics*, **51**, 104–114.

Shaheen, S., A. P. Cohen and E. W. Martin (2013) Public bikesharing in North America: Early operator understanding and emerging trends, *Transportation Research Record*, **2387**, 83–92.

Shaheen, S. A., N. D. Chan and H. Micheaux (2015) One-way carsharing's evolution and operator perspectives from the Americas, *Transportation*, **42**, 519–536.

Shaheen, S. A. and A. P. Cohen (2013) Carsharing and Personal Vehicle Services: Worldwide Market Developments and Emerging Trends, *International Journal of Sustainable Transportation*, **7**, 5–34.

Shaheen, S. A., A. P. Cohen and M. Jaffee (2018) Innovative Mobility Carsharing Outlook, *Technical Report*, Transportation Sustainability Research Centre, University of California, Berkeley.

Shaheen, S. A., A. P. Cohen and J. D. Roberts (2006) Carsharing in North America Market Growth, Current Developments, and Future Potential, *Transportation Research Record*, **1986**, 116–124.

Shaheen, S. A., C. Rodier, G. Murray, A. Cohen and E. Martin (2010) Carsharing and public parking policies: assessing benefits, costs, and best practices in North America, *Technical Report*, **CA-MTI-10-2612**, Mineta Transportation institute, San Jose, California.

Simma, A. and K. W. Axhausen (2001) Structures of commitment in mode use: A comparison of Switzerland, Germany and Great Britain, *Transport Policy*, **8** (4) 279–288.

Sioui, L., C. Morency and M. Trépanier (2013) How Carsharing Affects the Travel Behavior of Households: A Case Study of Montréal, Canada, *International Journal of Sustainable Transportation*, **7**, 52–69.

Smiley, D. (2016) Car2Go suspending business indefinitely in Miami, Miami Beach, *Miami Herald*.

Smith, G., J. Sochor and I. C. M. Karlsson (2018) Mobility as a Service: Development scenarios and implications for public transport, *Research in Transportation Economics*.

Sochor, J., I. C. M. A. Karlsson and H. Strömberg (2016) Trying out mobility as a service: Experiences from a field trial and implications for understanding demand, *Transportation Research Record*, **2542**, 57–64.

Sochor, J., H. Strömberg and I. C. M. A. Karlsson (2015) Implementing Mobility as a Service: Challenges in Integrating User, Commercial, and Societal Perspectives, *Transportation Research Record*, **2536**, 1–9.

Stasko, T. H., A. B. Buck and H. O. Gao (2013) Carsharing in a university setting: Impacts on vehicle ownership, parking demand, and mobility in Ithaca, NY, *Transport Policy*, **30**, 262–268.

Stata Press (2013) *Structural equation modeling reference manual*, version 13 edn., Stata Press, Texas.

StataCorp (2015) *Stata Statistical Software: Release 14*, StataCorp LP, College Station, TX.

Steer Davies Gleave (2016) Carplus annual survey of car clubs 2015/2016, *Technical Report*, Leeds.

Steer Davies Gleave (2017) Carplus Annual Survey of Car Clubs 2016/2017, *Technical Report*, Leeds.

Steininger, K., C. Vogl and R. Zettl (1996a) Car-sharing organizations - The size of the market segment and revealed change in mobility behavior, *Transport Policy*, **3** (4) 177–185.

Steininger, K., C. Vogl and R. Zettl (1996b) Car-sharing organizations: The size of the market segment and revealed change in mobility behavior, *Transport Policy*, **3** (4) 177–185.

Stillwater, T., P. L. Mokhtarian and S. A. Shaheen (2009) Carsharing and the Built Environment: Geographic Information System-Based Study of one U.S. Operator, *Transportation Research Record*, **2110**, 27–34.

Stopher, P. (1980) Captivity and choice in travel-behavior models, *Journal of Transportation Engineering*, **106**, 427–435.

Stopher, P., C. FitzGerald and M. Xu (2007) Assessing the accuracy of the Sydney Household Travel Survey with GPS, *Transportation*, **34** (6) 723–741.

Stopher, P. R. (1969) A probability model of travel mode choice for the work journey, *Highway Research Record*, 57–65.

Suiker, S. and J. van den Elshout (2013) Wirkungsmessung Einführung car2go in Amsterdam, paper presented at the *Nationaler Verkehrswissenschaftskongress*, Amsterdam.

Swait, J. and M. Ben Akiva (1987) Incorporating random constraints in discrete models of choice set generation, *Transportation Research Part B*, **21B** (2) 91–102.

Swait, J. and J. J. Louviere (1993) The role of the scale parameter in the estimation and use of multinomial logit models, *Journal of Marketing Research*, **30** (3) 305–314.

Swiss Federal Statistical Office (BFS) (2006) *Ergebnisse des Mikrozensus 2005 zum Verkehrsverhalten*, Swiss Federal Statistical Office (BFS), Neuchatel.

Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE) (2012) *Mobilität in der Schweiz - Ergebnisse des Mikrozensus Mobilität und Verkehr 2010*, Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), Neuchatel and Berne.

Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE) (2017) *Verkehrsverhalten der Bevölkerung - Ergebnisse des Mikrozensus Mobilität und Verkehr 2015*, Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), Neuchatel and Berne.

Tanner, R. and D. Bolduc (2014) The Multiple Discrete-Continuous Extreme Value Model (MDCEV) with fixed costs, *Procedia - Social and Behavioural Sciences*, **111**, 390–399.

Train, K. (1980) A structured Logit model of auto ownership and mode choice, *The Review of Economic Studies*, **47**, 357–370.

Train, K. E. (1986) *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*, MIT Press.

Train, K. E. (2003) *Discrete Choice Methods with Simulation*, Cambridge, MA: Cambridge University Press.

Van der Straeten, K., A. Trannoy, N. Picard and C. Hagneré (2003) L'importance des incitations financières dans l'obtention d'un emploi est-elle surestimée?, *Économie & prévision*, **160** (4) 49–78.

van Eggermond, M., A. Erath and K. W. Axhausen (2016) Vehicle Ownership and Usage in Switzerland: Role of Micro- and Macroaccessibility, paper presented at the *95th Annual Meeting of the Transportation Research Board*, Washington, D.C.

van Wee, B. (2009) Self-Selection: A Key to a Better Understanding of Location Choices, Travel Behaviour and Transport Externalities?, *Transport Reviews*, **29** (3) 279–292.

Vrtic, M., K. W. Axhausen, F. Rossera and R. Maggi (2003) Verifizierung von Prognosemethoden im Personenverkehr, *Research Report*, Swiss Railways, Swiss Federal Office for Spatial Development (ARE), IVT, ETH Zurich, Institute for Economic Research (IRE), University of Lugano, Zurich.

Wang, F. and C. L. Ross (2017) New potential for multimodal connection: exploring the relationship between taxi and transit in New York City (NYC), *Transportation*.

Wargelin, L., P. Stopher, J. Minser, K. Tierney, M. Rhindress and S. O'Connor (2012) GPS-Based Household Interview Survey for the Cincinnati Ohio Region, *Technical Report*, Abt SRBI Inc., New York.

Wooldridge, J. M. (2002) *Econometric Analysis of Cross Section and Panel Data*, MIT Press, Cambridge.

Yamamoto, T. (2009) Comparative analysis of household car, motorcycle and bicycle ownership between Osaka metropolitan area, Japan and Kuala Lumpur, Malaysia, *Transportation*, **36** (3) 351–366.

Zha, L., Y. Yin and H. Yang (2016) Economic analysis of ride-sourcing markets, *Transportation Research Part C*, **71**, 249–266.

Zhao, J., W. Deng and Y. Song (2014) Ridership and effectiveness of bike-sharing: The effects of urban features and system characteristics on daily use and turnover rate of public bikes in China, *Transport Policy*, **35**, 253–264.

Ziemke, D., S. Metzler and K. Nagel (2017) Modeling bicycle traffic in an agent-based transport simulation, *Procedia Computer Science*, **109**, 923–928.

ARTICLES IN THIS DISSERTATION

Becker, H., M. Balac, F. Ciari and K. W. Axhausen (2019) Assessing the welfare impacts of MaaS: A case study in Switzerland, *Transportation Research Part A*. DOI: 10.1016/j.tra.2019.09.027.

Becker, H., F. Ciari and K. W. Axhausen (2017a) Comparing car-sharing schemes in Switzerland: User groups and usage patterns, *Transportation Research Part A*, **97**, 17–29.

Becker, H., F. Ciari and K. W. Axhausen (2017b) Modelling free-floating car-sharing use in Switzerland: A spatial regression and conditional logit approach, *Transportation Research Part C*, **81**, 286–299.

Becker, H., F. Ciari and K. W. Axhausen (2018) Measuring the car ownership impact of free-floating car-sharing - A case study in Basel, Switzerland, *Transportation Research Part D*, **65**, 51–62.

Becker, H., A. Loder, B. Schmid and K. W. Axhausen (2017c) Modeling car-sharing membership as a mobility tool: A multivariate Probit approach with latent variables, *Travel Behaviour and Society*, **8**, 26–36.

FURTHER PEER-REVIEWED JOURNAL ARTICLES

Balac, M., H. Becker, F. Ciari and K. W. Axhausen (2019) Modeling competing free-floating carsharing operators – A case study for Zurich, Switzerland, *Transportation Research Part C*, **98**, 101–117.

Becker, H., G. Bison, B. Blau, Z. Chowdhuri, J. Eikenberg, M. Fertl, K. Kirch, B. Lauss, G. Perret, D. Reggiani, D. Ries, P. Schmidt-Wellenburg, V. Talanov, M. Wohlmuther and G. Zsigmond (2015) Neutron production and thermal moderation at the PSI UCN source, *Nuclear Instruments and Methods in Physics Research Section A*, **777**, 20–27.

Bösch, P., F. Becker, H. Becker and K. W. Axhausen (2018) Cost-based Analysis of Autonomous Mobility Services, *Transport Policy*, **64**, 76–29.

Ciari, F. and H. Becker (2017) How disruptive can shared mobility be? A scenario-based evaluation of shared mobility systems implemented at large scale, *Disrupting Mobility*, 51–63.

Guidon, S., H. Becker, H. Dediu and K. W. Axhausen (2019) Electric bicycle-sharing: a new competitor in the urban transportation market?: An empirical analysis of transaction data, *Transportation Research Record*, **2673** (4) 15–26.

Marra, A., H. Becker, K. W. Axhausen and F. Corman (2019) Developing a passive GPS tracking system to study long-term travel behavior, *Transportation Research Part C*, **104**, 348–368.

Meyer, J., H. Becker, P. Bösch and K. W. Axhausen (2017) Autonomous vehicles: The next jump in accessibilities?, *Research in Transportation Economics*, **62**, 80–91.

Meyer de Freitas, L., H. Becker, M. Zimmermann and K. W. Axhausen (2019) Modelling intermodal travel in Switzerland: A recursive logit approach, *Transportation Research Part A*, **119**, 200–213.