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Electric bicycle-sharing: a new competitor in the urban transportation market?

An empirical analysis of transaction data

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Abstract

Electric bicycles (e-bikes) are a new addition to bicycle-sharing and may improve its competitiveness. E-bikes allow for higher speeds at a higher level of comfort than conventional bicycles and compared to traditional bicycle-sharing, e-bike-sharing is better positioned to complement or compete with existing public transportation, or to even challenge established taxi services. Until this point, there has been no empirical analysis of e-bike-sharing.

Eight months of transaction data from a free-floating e-bike-sharing system in Zurich, Switzerland were used to study the market position of e-bike sharing and drivers of demand.

The results of the analysis indicate that a large proportion of the trips were commuting, and that the distance range of e-bike-sharing trips overlaps with the distance ranges of traditional public transportation and taxi services. Intensity of use was sensitive to precipitation. Spatial regression modeling indicates that economic and social activity, public transportation service quality and the availability of bicycle infrastructure are key drivers of demand for free-floating e-bike-sharing.

Given the substantial structural differences in demand and supply patterns, an attempt is made to define a new, fifth generation of bicycle-sharing schemes.

Keywords: bicycle-sharing, e-bike-sharing, urban transportation, demand analysis, spatial regression

1. Introduction

Since the first bicycle-sharing system was introduced in Amsterdam in 1965, the number of systems has grown substantially all over the world. Moreover, the services have evolved, using technological advances to address problems and improve the user experience. In the literature, systems were classified into four generations (Shaheen et al., 2010). The first generation started with theft-prone free bicycles and continuous innovation led to fourth generation large-scale schemes like Capital Bikeshare in Washington, DC, which operate docking stations across large service areas. In recent years, free-floating services offering access to e-bikes have emerged, defining a fifth generation of bicycle-sharing.

There are two innovations with this new generation that have brought about profound changes. While e-bikes allow for longer distances to be travelled at higher speeds and with less exertion (especially in hilly terrain), re-charging of the battery requires extra service effort or infrastructure. The free-floating service potentially translates into a better user experience (no more full stations at the destination), but may also result in lower reliability at the trip origin.

Substantial research has already been conducted to understand user groups, demand patterns and the market position of existing bicycle-sharing services (Fishman et al., 2013; Fishman, 2016). Bicycle-sharing thrives where it offers convenient service with a dense network of stations (El-Assi et al., 2017; Rixey, 2013). In contrast to other shared modes of transportation, such as car-sharing, bicycle-sharing seems to draw a substantial share of its demand from traditional public transportation (Fishman et al., 2014a; Campbell and Brakewood, 2017). Generally, two main customer groups are served: annual subscribers using it for work trips and leisure travellers (tourists) only making a few trips per year (Fishman et al., 2015; Wergin and Buehler, 2017). Spatiotemporal demand patterns are not symmetric, making relocations necessary (Nair et al., 2013). In particular, stations at elevated locations are unattractive destinations (Faghieh-Imani et al., 2017b). The two innovations of e-bikes and a free-floating service, however, could change the above patterns. Shared bicycles can become competition for private cars and taxi services, as the electric motor helps to overcome gradients and free-floating operations make the service seamless. It has been shown for car-sharing that such profound changes in the service can lead to substantially different (and larger) customer groups and change usage patterns (Becker et al., 2017a).

1 In this paper, eight months of transaction data was analyzed from *Smide*,
2 a high-end e-bike-sharing system in Zurich, Switzerland. The e-bike-sharing
3 market is discussed and the competitive position of e-bike-sharing is com-
4 pared to other modes of transportation. The analysis takes into account
5 time of day, terrain elevation and weather. Furthermore, a spatial regression
6 model was used to analyze the drivers of demand for e-bike-sharing. The re-
7 sults showed the differences between traditional and e-bike-sharing in terms
8 of market potential. The effect of e-bike-sharing on the overall transporta-
9 tion system was also investigated. Based on these insights, an attempt was
10 made to define the next generation of bicycle-sharing services.

11 **2. Background**

12 Bicycle-sharing has seen substantial growth in recent decades, most of
13 which was due to technology-driven innovations making the services more
14 attractive and operations more robust. As a result, modern bicycle-sharing
15 schemes only have few things in common with early implementations like
16 the *White Bikes* in Amsterdam in 1965. Shaheen et al. (2010) provide an
17 overview of early implementations and suggested classifying schemes into
18 four generations. The first generation offered free access to a fleet of bi-
19 cycles, which were distributed across a city. However, because the bicycles
20 did not have locks, the system was prone to theft. Second generation ser-
21 vices addressed this issue by introducing a coin-deposit system, where users
22 had to pick up a bicycle at a station, but needed to leave a small deposit.
23 While this reduced theft, vandalism was still an issue. The third genera-
24 tion brought user-identification and required substantial deposits to further
25 reduce theft and vandalism. Pricing concepts were then introduced with
26 annual subscriptions for frequent users or trip-based charges for leisure trav-
27 elers. Imbalances in demand led to unfavorable station occupancy (full or
28 empty), which deteriorated service attractiveness, as did a lack of integration
29 with public transportation. Fourth generation schemes address such issues
30 by performing rebalancing of bicycles and integrating payment mechanisms
31 that can be used to access public transportation services (Fishman et al.,
32 2013). Yet, fourth generation schemes still relied on conventional bicycles
33 and fixed stations.

34 Impact and drivers of demand for third and fourth generation systems
35 have been studied extensively in the literature. Most research was aimed at
36 identifying factors influencing demand patterns, user groups and the impact

1 on other modes (with a focus on interactions with public transport). A com-
2 mon approach for identifying drivers of demand is to analyze actual trip data
3 using (spatial) regression techniques or destination choice models. For New
4 York City, Noland et al. (2016) and Faghih-Imani and Eluru (2016) identi-
5 fied population and employment density as drivers of demand. Proximity to
6 busy subway stations and denser bicycle infrastructure were also found to
7 increase station utilization. Recent research suggests that the latter is more
8 important than system size (Médard de Chardon et al., 2017). However, sub-
9 stantial short-term variations were induced by weather effects, in particular
10 precipitation (Noland et al., 2016; Faghih-Imani and Eluru, 2016). These
11 results were confirmed for other cities with the extension that proximity to
12 restaurants and points of interest increased demand, whereas uphill desti-
13 nations were travelled to less frequently (El-Assi et al., 2017; Faghih-Imani
14 et al., 2017b). Caulfield et al. (2017) showed that the patterns also hold for
15 smaller cities, but with shorter trip distances.

16 User characteristics associated with membership and use of bicycle-sharing
17 services were explored using surveys. In Washington, DC, bicycle-sharing
18 users were found to be mostly younger females with a lower household income
19 (Buck et al., 2013). The results were extended by Fishman et al. (2014b)
20 where users in Melbourne and Brisbane lived in smaller activity spaces with
21 inferior public transportation supply. Proximity to bicycle-sharing stations
22 and relatively higher incomes were found to increase the propensity for mem-
23 bership in those two cities. A substantial difference in usage patterns was
24 found for these locations, where holders of an annual subscription were found
25 to mostly use the service for commuting, but leisure travellers took longer
26 and slower trips (Wergin and Buehler, 2017).

27 Bicycle-sharing has been shown to be preferred for many trips. In an
28 analysis for New York City, Faghih-Imani et al. (2017a) compared travel
29 times by bicycle-sharing and taxi. The results indicated that bicycle-sharing
30 was on par with or faster than taxis for trips less than 3 km. Yet, bicycle-
31 sharing has become a substitute for public transportation, with bus rider-
32 ship decreasing by 2% after the bicycle-sharing scheme was expanded into
33 the respective neighbourhoods (Campbell and Brakewood, 2017). A similar
34 effect was observed in other studies (Fishman et al., 2013). Depending on
35 the city characteristics, the low substitution of private car travel may even
36 translate into a net increase in vehicle miles travelled, when taking into ac-
37 count relocation of bicycles (Fishman et al., 2014a). However, substitution
38 of public transport trips is not necessarily disadvantageous. For free-floating

1 car-sharing, it was found that the replaced public transportation trips had
2 particularly long travel times or included transfers (Becker et al., 2017b).
3 In a similar vein, bicycle-sharing may also be used to complement public
4 transportation, where it is inefficient. Insights from the Chinese cities of
5 Hangzhou and Ningbo confirm this finding (Yang et al., 2018).

6 In recent years, e-bikes have entered the mass-market and have also be-
7 come part of bicycle-sharing systems. The electric motorization addresses key
8 limitations of current systems. It allows for higher speeds and thus longer trip
9 distances and it is substantially less strenuous to ride uphill. Free-floating
10 operations provide more seamless trips and may therefore attract even higher
11 ridership. In a way, electric motorization places free-floating e-bike-sharing
12 between conventional bicycle-sharing and free-floating car-sharing. Riders
13 are still directly exposed to the weather and cannot carry bulky items, how-
14 ever, the scheme can be used for flexible trips across the city at the effective
15 speed of a car (and without the need to search for parking). Given these
16 substantial advances in the service, insights gained on user groups and usage
17 patterns of conventional bicycle-sharing schemes may not be transferable to
18 free-floating e-bike-sharing (c.f. Becker et al. (2017a)). As a result, mode
19 substitution and impact on vehicle-miles travelled may be different.

20 Cairns et al. (2017) observed a decrease in vehicle miles travelled (VMT)
21 of 20% in a trial in Brighton, UK, where participants were equipped with
22 e-bikes over a six to eight week period. Fyhri and Fearnley (2015) reported
23 the results of a trial in Norway, in which e-bikes were given to 66 randomly
24 selected participants. The availability of e-bikes increased the amount of
25 cycling, both in terms of distance and number of trips. The high substi-
26 tution rate of private car trips in the Brighton trial suggests that e-bike-
27 sharing might have a different effect on car usage than traditional bicycle-
28 sharing schemes. A first stated-preference approach on e-bike-sharing in
29 China further confirmed that e-bike-sharing is attractive for longer trip dis-
30 tances, but suggested that e-bike-sharing was only attractive to certain socio-
31 demographic segments (Campbell et al., 2016). No empirical data has been
32 used to test the above hypotheses thus far. This research aims to address this
33 gap by analyzing transaction data of a free-floating e-bike-sharing system.

34 **3. Descriptive Analysis**

35 This section provides an overview of the data sources and the regional
36 context, presents descriptive statistics of the booking data, and shows the

1 potential market niche for e-bike-sharing with respect to trip distance.

2 *3.1. Data Sources and Regional Context*

3 The analysis in this paper is based on the booking and trip data of a free-
4 floating e-bike-sharing system in Zürich, Switzerland called “Smide,” which
5 began operation in October 2016. Smide is a high-end e-bike-sharing system
6 of “Stromer ST2” e-bikes with an engine power of 800 Watt and a retail
7 price of CHF 7000 (equal to \$7000 US in May 2018). The e-bikes reach a
8 maximum speed of 45 km/h, however, the speed was reduced to 35 km/h by
9 the operator for safety reasons. The booking price is currently CHF 5 for
10 20 minutes and usage is charged pro rata on a per-minute basis. 200 e-bikes
11 are part of the system and the area of operation covers a large share of the
12 municipal area of the city of Zürich (see Figure 2). The user interface consists
13 of a smartphone application that displays the current positions of the e-bikes
14 and the geofence. Users can prepay booking time, book and unlock e-bikes,
15 and access the history of previous bookings. To assist with rebalancing, the
16 system features so called “bonus zones”. Users who decide to end a booking
17 in a bonus zone receive a specific amount of minutes (five or ten minutes) of
18 additional booking time. The system also features one charging station and
19 users who end a trip at the charging station and plug in the charging cable
20 also receive a bonus of five minutes. The batteries of the bikes in the system
21 are regularly changed by the operator such that the number of bikes with
22 low battery levels are minimized.

23 The main dataset analyzed in this paper consisted of 99,094 e-bike-sharing
24 trips from April to November 2017. After data cleaning (removal of trips
25 without distances and merging adjacent trips), 72,648 trips remained. To
26 compare the trip data to alternative urban modes of transportation, addi-
27 tional data was obtained from the Swiss national household travel survey,
28 “Mikrozensus Mobilität und Verkehr 2015” (MZMV) (Swiss Federal Statis-
29 tical Office (BFS), 2017a). The MZMV is a computer assisted telephone
30 interview with a sample size of 57,090 subjects that is conducted every five
31 years across Switzerland. For each subject, the dataset includes detailed
32 information about all trips of a randomly chosen day, including distance,
33 geocoded origins and destinations, and chosen mode of transportation for all
34 stages of trips (the dataset included 279,173 stages, 12,215 of which began
35 and ended in the city of Zurich).

36 Zürich is a medium-sized city with approximately 400,000 inhabitants
37 (political city boundaries) and 1.8 million inhabitants in its metropolitan

1 area. The Zürich metropolitan area is Switzerland’s economic center, where
2 approximately 200,000 people commute to and more than half use pub-
3 lic transportation. Zürich is located in the pre-Alps and exhibits a max-
4 imum elevation difference of ca. 480 m within its municipal area. Pub-
5 lic transportation service quality is considered very high, with 4.7 public
6 transportation stops per square kilometre and a regulation that all residents
7 should be able to reach a public transportation stop within 400 meters, the
8 city’s goal is 300 meters. (For general information about the city refer to
9 <https://www.stadt-zuerich.ch/>, last accessed: July 2018.) In 2017, three
10 bicycle-sharing systems were available in Zürich: O-Bike (meanwhile discon-
11 tinued), a station-based system operated by the city of Zürich (both without
12 e-bikes), and Smide.

13 *3.2. Trip Data Overview*

14 Figure 1 shows an overview of the Smide trip data. A mean number of 305
15 trips were made on an average day (with a median of 306). The standard
16 deviation is very high with 142, mainly because the system was growing
17 strongly between April and July. (The mean number of trips after July was
18 364 with a standard deviation of 114.) The mean trip distance was 2.5 km
19 with a mean duration of 10.3 min. Peak demand was reached between 6 pm
20 and 8 pm and a morning peak was observed between 7 am and 8 am. The
21 two distinct peaks and the fact that weekdays exhibited a higher demand
22 than weekend days indicated that a significant share of the demand was
23 commuting. The morning (7 am until 10 am) and the afternoon (2 pm until
24 5 pm) accounted for 46% of the total demand (20% and 26%, respectively),
25 the noon (11 am until 1 pm) accounted for 16%, and the evening (6 pm until
26 9 pm) accounted for 25%. Night (10 pm until 1 am) and late night (1 am
27 until 6 am) trips accounted for 12% percent of the demand (7% and 5%,
28 respectively). The majority of the demand therefore arose during times of
29 the day when public transportation service quality was also high. However,
30 in Zürich, public transportation operation stops at 1 am on weekdays and
31 there is only a limited late night service on Fridays and Saturdays. Late at
32 night, public transportation would, therefore, not have been an alternative
33 to Smide.

34 One advantage of e-bikes is the lower sensitivity towards terrain eleva-
35 tions. Figure 1 d) shows the distribution of elevation differences between
36 destinations and origins. The figure indicates that trips were not primarily
37 up- or downhill. Also relevant for cyclists is the sum of positive elevation

1 differences along the chosen routes, which were determined with the Google
 2 Elevation API. (<https://developers.google.com/maps/documentation/elevation/>, last accessed: July 2018.) For each path, 20 points were sam-
 3 eled. The median sum of positive elevation differences was 14.7 m with a
 4 mean of 31 m. Thus, e-bikes were used independent of elevation.
 5

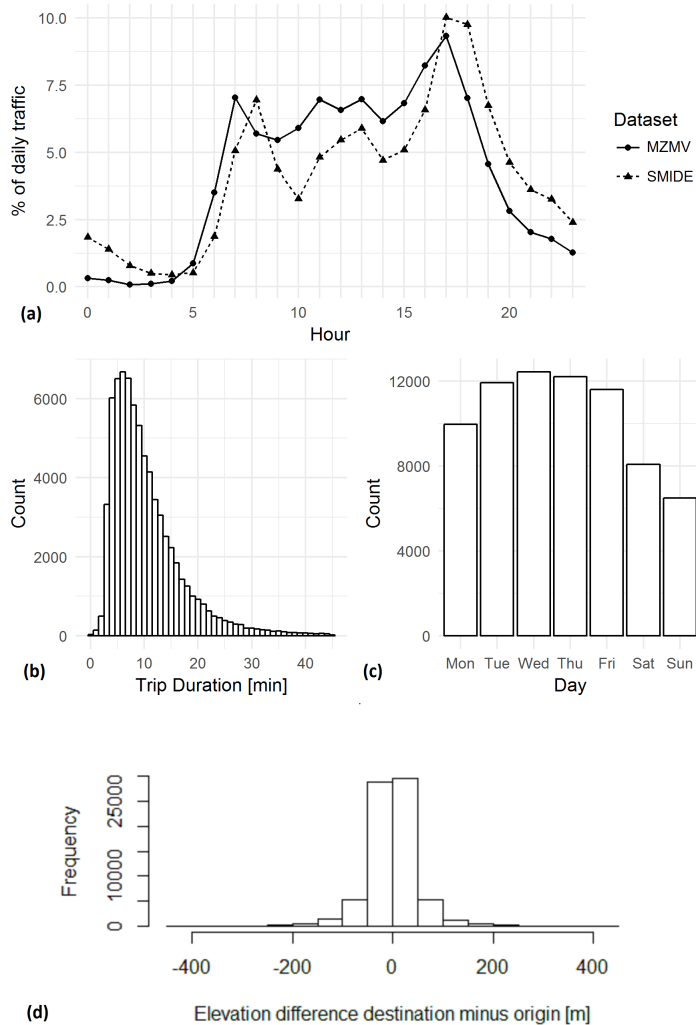


FIGURE 1: Smide trip data overview: (a) % of daily traffic by hour (household travel survey (MZMV) vs. Smide), (b) trip duration distribution, (c) trip frequencies by day of the week, (d) elevation difference distribution (desination minus origin).

1 Figure 2 shows the spatial distribution of rental starting points in the
 2 city of Zürich. A high concentration of rental starts was observed in district
 3 1. District 1 is the major business district of Zürich, which also includes the
 4 two universities and only accounts for 1.4% of the total population of the city
 5 (5,728 of 423,310 residents). This supports the conclusion that commuters
 6 were a major segment of demand. The spatial distribution changes for night
 7 and late night bookings. At night, a major share of bookings occurred in
 8 district 4, which is one of Zürich’s main nightlife areas. This indicates that
 9 Smide e-bike-sharing was used to substitute (or complement) traditional public
 10 transportation when service quality was lower.

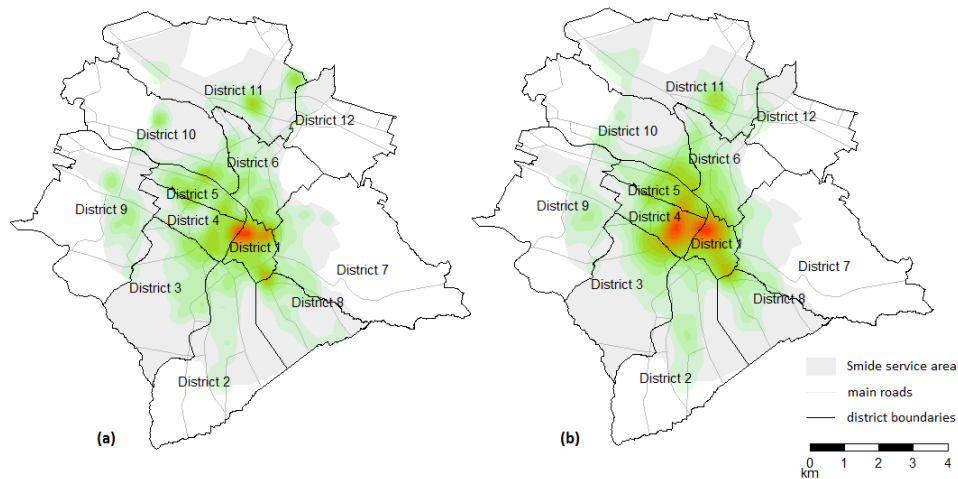
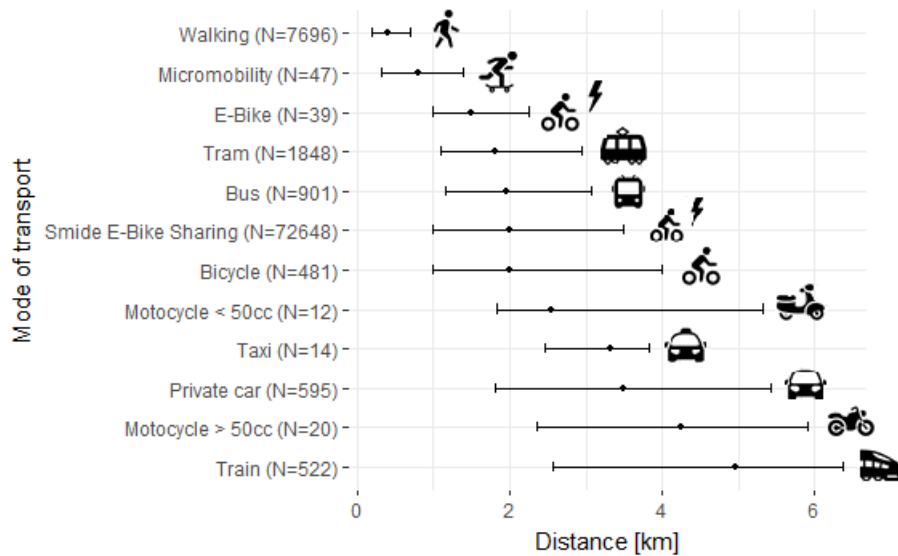


FIGURE 2: (a) Spatial distribution of rental start locations (all bookings), and (b) late night bookings (10 pm until 6 am).

11 3.3. Market Segmentation: Analysis of Trip Distributions

12 In order to analyze the market position of e-bike-sharing, the trip distance
 13 distribution was compared to those of alternative urban modes of transporta-
 14 tion. Figure 3 shows the median, the lower quartile and the upper quartile
 15 of the distance distributions of trips with origins and destinations in the city
 16 of Zürich. The figure shows, which modes of transportation served similar
 17 trip distances to e-bike-sharing. The trip data for the alternative modes was
 18 obtained from the Swiss household travel survey from the year 2015 (Swiss
 19 Federal Statistical Office (BFS), 2017a). All trips that started or ended in
 20 the city of Zurich were included in this comparison.

1 E-bikes and e-bike-sharing trips were in the same distance range as tradi-
 2 tional public transportation (buses and trams), cycling with a private bicycle,
 3 and small motorbikes. Taxi trips were longer than e-bike-sharing trips at the
 4 median, but the distance range of taxi trips was also not atypical for e-bike-
 5 sharing. The comparison of modes indicated that e-bike-sharing was able to
 6 substitute a wide range of trips of other modes of transportation.



Data source: MZMV 2015, BFS; Smide; Icons: <https://icons8.com/>

FIGURE 3: Distance ranges in the urban passenger transportation market: median, and the upper/lower quartiles.

7 Although not the focus of this paper, it is interesting to note that mi-
 8 cromobility (skateboards, kickboards etc.) efficiently fills the gap between
 9 walking and cycling.

10 3.4. Comparison of E-bike-sharing Trips with Alternative Modes

11 Smide e-bike-sharing trip times were compared to the alternatives taxi,
 12 transit and walking. Trip times for the alternative modes of transporta-
 13 tion were estimated with the Google Directions API. (<https://developers.google.com/maps/documentation/directions>, last accessed: July 2018.)
 14 The comparison of trip times for the Smide data are shown in Table 1. E-
 15 bike-sharing was amongst the fastest transportation options, and only a taxi
 16

1 would have been faster at the median. 18.2% of transit trips involved at
 2 least one transfer, and in 18.1% of the cases the trip time corresponded to
 3 the walking time, as public transportation was not a feasible option. For
 4 transit, walking time was included, while for taxi and Smide, the time cor-
 5 responded to the actual trip time. The total trip time of Smide would also
 6 include walking time to the nearest e-bike. For taxis, the total trip time
 7 would also include waiting time. For transit, transfers constitute a disutility
 8 and the time between desired departure time and actual departure time was
 9 not considered. Therefore, the times in Table 1 are generally rather opti-
 10 mistic. Furthermore, it is likely that Smide was only chosen if an e-bike was
 11 close to the desired origin of the trip and therefore, the data is subject to
 12 an unknown amount of censored demand. Thus, as a comparison, 12,215
 13 trips from the Swiss household travel survey (MZMV) were also analyzed
 14 (see Table 1 “MZMV data”). The Google Directions API was used to gener-
 15 erate proxy travel times for Smide. For MZMV trips in the city of Zürich,
 16 Smide was the fastest mode at the median, and at the first quartile. At the
 17 mean and at higher quantiles, a private car or taxi was faster. This can be
 18 explained by the fact that an average trip from the Swiss household travel
 19 survey is only 1.5 km (compared to the average Smide trip distance of 2.5
 20 km) and the car plays out its strengths at higher trip distances.

TABLE 1: Comparison of Smide trip times with potential alternative modes of transportation. Trip times for driving, transit, walking were determined with the Google Distances API. Only trip durations over one minute were considered.

Unit: min		1st Quartile	Median	Mean	3rd Quartile
Smide data	Smide	6.6	9.7	11	14
	Taxi	4.9	7.7	8.3	11.0
	Transit	8.9	13.7	14.9	19.8
	Walking	13.6	24.5	29.1	40.0
MZMV data	Smide*	1.6	3.7	6.2	8.3
	Taxi	1.9	4.3	5.4	7.7
	Transit	2.9	5.4	7.3	9.6
	Walking	3.4	7.9	15.7	21.5

*Google bicycling routing as proxy for Smide.

1 4. The Effect of Weather and Day of the Week on Daily Bookings

2 A negative binomial regression model was estimated to analyze the effect
3 of weather and day of the week on the number of daily bookings. The weather
4 data was obtained from the Swiss Federal Office of Meteorology and Clima-
5 tology for one representative station in the city of Zürich. (Weather data
6 for Switzerland can be found here: <https://www.meteoschweiz.admin.ch/>,
7 last accessed: July 2018.) A dummy for the weekend days was also included
8 in the model. The weather data included temperature (in degrees Celsius),
9 a precipitation dummy (1 if there was precipitation), and solar radiation
10 (W/m^2). Because the total number of bookings has greatly increased be-
11 tween April and July, and only stabilized after July, the models were esti-
12 mated for a subset of the booking data from July to November 2017. During
13 this period a mean of 364 bookings per day (with a median 356) were made.

14 Temperature, precipitation, and the weekend dummy had highly signifi-
15 cant and substantive effects on the number of bookings (see Table 2). Solar
16 radiation was significant, but not substantive. The theta parameter of the
17 negative binomial model indicated that there was significant overdispersion
18 with respect to a Poisson model and thus a negative binomial model was
19 appropriate. With the other parameters at the mean, precipitation reduced
20 the number of bookings by 64 (-17%). On the weekend, demand decreased
21 by 149 bookings (-37%).

TABLE 2: Regression models for the number of daily bookings.

	Negative binomial model	
	Coef.	<i>SE</i>
number of bookings		
temperature	0.01 **	0.01
solar radiation	0.00 *	0.00
precipitation dummy	-0.18 ***	0.03
weekend dummy	-0.46 ***	0.04
Constant	5.84 ***	0.04
θ	29.72 ***	3.69
N	152	
AIC	1 719	
LL model	-853.6	
LL null model	-935.0	
McFadden's Pseudo R^2	0.1	
Significance codes: 0.1 * 0.05 ** 0.01 ***		

1 5. External Drivers of Demand

2 5.1. Data

3 To study external drivers of demand for free-floating e-bike-sharing, the
4 effect of spatial attributes was analyzed using regression techniques. To this
5 end, trip start points were aggregated to a 300 meter grid covering the whole
6 service area (593 zones). It was assumed that this corresponded to the max-
7 imum distance travellers were willing to walk to access a bike.

8 In addition, spatial attributes were obtained from various open data
9 sources: information on population size (*popSize* in thousands) and work
10 places (*workPlace* in thousands) were obtained from the official Swiss popu-
11 lation and enterprise statistics (Swiss Federal Statistical Office (BFS), 2017b,
12 2016). The data were available at hectare resolution; for the raster cells, the
13 corresponding averages were used. Service levels for public transportation is
14 defined by the Swiss standard SN640290 (*highPTlevel* indicates the highest
15 level “A”) and were obtained as shapefiles from the Swiss national open data
16 portal (Swiss open data portal: <https://opendata.swiss>, last accessed:
17 July 2018.) Information on the number of holders of the national season
18 ticket (GA) for public transportation (*GAperInh* providing the percentage
19 of GA holders among the population) was available from the same source,
20 but was only available at the level of ZIP codes. Zurich’s 25 ZIP-code areas
21 largely correspond to subdivisions of the different neighborhoods. Income
22 levels (*income* in 1 000 CHF) were available for the 34 statistical areas of the
23 city of Zurich from the city’s open data portal (Open data portal of the city
24 of Zurich: <https://data.stadt-zuerich.ch/>, last accessed: July 2018.)
25 For this analysis, the median taxable annual income of singles was used (the
26 actual gross income usually is substantially higher). From the same source,
27 the locations of all registered bars and restaurants were available and ag-
28 gregated to the raster cells (*gastronomy* gives the count per zone). Further
29 leisure facilities (such as sports facilities or cinemas) were available, but not
30 significant in the later modelling process. A shapefile with the city’s bicycle
31 infrastructure was obtained from the same source. *bikeInfra* denotes the total
32 length (in km) of dedicated bicycle infrastructure within the zone. *PTpas-*
33 *sengers* indicates the total number of people boarding or alighting a bus or
34 tram in the zone during an average work day (also available from the city’s
35 open data portal). The distances between the respective zone and the closest
36 urban rail station or the main train station, respectively, were calculated and
37 indicator variables defined, which denoted a maximum distance of 200 m to

1 an urban rail station (*urbanRail200*) and 500 m to the main train station
 2 (*HB500*). The variables are summarized in Table 3.

TABLE 3: Summary of attributes used in demand model.

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max
number of rentals	0	12	60	119.3	161	1605
popSize	0.0	0.008	0.052	0.073	0.113	0.394
workPlace	0.0	0.003	0.006	0.085	0.470	2.012
income	30.1	38.5	42.5	43.2	48.4	60.0
gastronomy	0.0	0.0	1.0	3.5	3.0	71
bikeInfra	0.0	0.8	1.3	1.3	1.7	3.5
PTpassengers	0.0	0.0	0.0	3.6	4.9	96.9
GAperInh	0.0	2.5	2.7	3.5	4.4	7.8
highPTlevel	22% of the zones					
urbanRail200	18% of the zones					
HB500	3% of the zones					

3 Figure 4 shows the spatial distribution of trip start locations. It indicated
 4 that peak demand is in the city center and decreases towards the borders of
 5 the service area. Generally, the drop in demand was more substantial towards
 6 the North and the West. Locations without any rentals correspond to forests,
 7 hills/creeks or railway/motorway infrastructure.

8 5.2. Methodology

9 As shown in Table 3, the response variable (number of rentals) does not
 10 follow a normal distribution. Hence, a count-data model (e.g. negative
 11 binomial) must be used or the response variable needs to be transformed
 12 to allow application of linear regression. Since Figure 4 already indicates a
 13 spatial structure in the data, the latter option was chosen (spatial models for
 14 count data are still rare in the literature). Thus, a Box-Cox transformation
 15 (Box and Cox, 1964) was applied with λ estimated as 0.303.

The linear regression model is presented in Table 4. Although the relatively large R_{adj}^2 indicated a high explanatory power, the model was not valid given a significant level of spatial autocorrelation of the residuals (Moran I standard deviate = 2.7, $p = 0.006$). A Lagrange-Multiplier test (Anselin et al., 1996) indicated significant spatial dependence for the dependent variable ($LM_{lag} = 18.0$, $df = 1$, $p < 2.2 \cdot 10^{-5}$). However, spatial autocorrelation

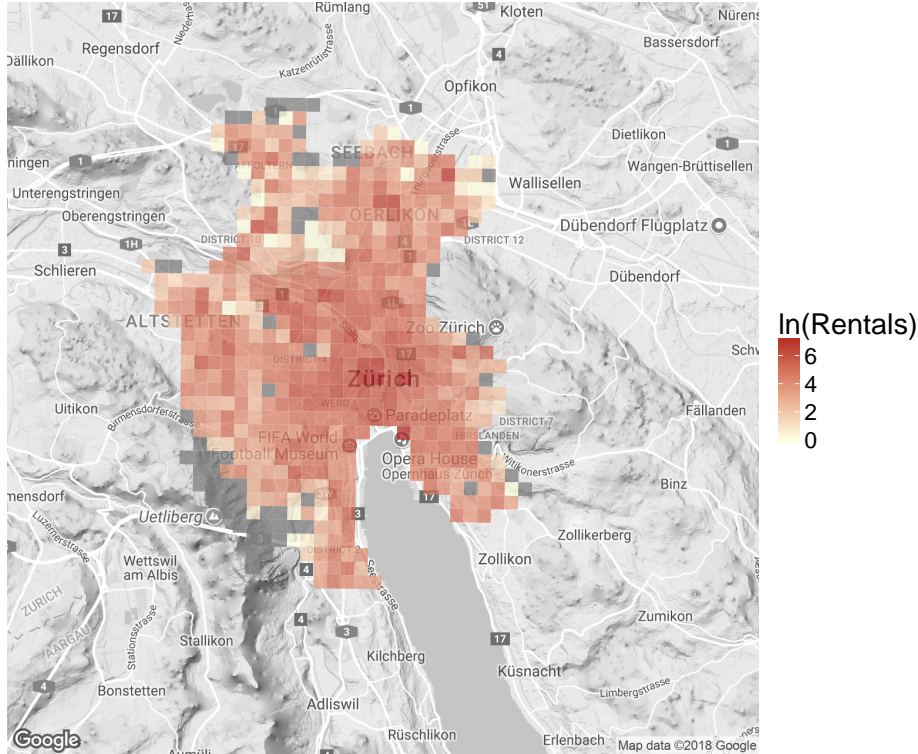


FIGURE 4: Number of reservations (logarithm) per raster cell from yellow (low) to dark red (high). Zones with no observations are given in grey.

of the disturbances was weak ($LM_{err} = 6.9$, $df= 1$, $p = 0.01$). Therefore, a linear Cliff-and-Ord-type (Cliff and Ord, 1973) SAR model of the form

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

- 1 was estimated. Here, W denotes the row-standardized spatial weights matrix
- 2 for eight nearest neighbors. The neighboring zones were chosen to cover a
- 3 300 m perimeter around the respective zone, which was assumed to be an
- 4 acceptable walking distance for a free-floating bicycle-sharing user. This
- 5 way, the SAR model formulation accounted for local spillover effects (e.g.
- 6 a bicycle is not available in the origin zone, but in one of the neighboring
- 7 zones).

1 The model was estimated using Maximum Likelihood. Again, the Box-
2 Cox transformed response variable was used. The results are presented in
3 Table 4 along with the simple linear regression model. Comparing the AIC
4 values, the spatial model fit the data substantially better than the simple
5 regression model described above. Not accounting for spatial autocorrelation
6 in the disturbances was justified ($LM_{err} = 0.02$, $p = 0.9$).

TABLE 4: Regression models for free-floating bicycle-sharing demand.

	simple linear model		spatial lag model	
	Coef.	<i>t</i>	Coef.	<i>t</i>
number of departures				
popSize (in thousands)	21.62 ***	9.18	13.18 ***	6.55
workPlace (in thousands)	2.76 ***	3.59	1.63 **	2.53
highPTlevel (dummy)	2.14 ***	4.45	1.14 ***	2.82
PTpassengers (count)	0.16 ***	5.18	0.16 ***	6.49
income (in 1000 CHF)	0.18 ***	7.10	0.07 ***	3.23
gastronomy (count)	0.13 ***	4.58	0.05 *	1.92
bikeInfra (km)	1.09 ***	3.55	0.89 ***	3.47
urbanRail200 (dummy)	1.54 ***	3.41	0.82 **	2.14
HB500 (dummy)	4.43 ***	3.70	1.69 *	1.67
GAperInh (percent)	0.28 **	2.30	-0.06	-0.61
(Intercept)	-6.02 ***	-5.98	-3.27 ***	-3.83
λ	-		0.60 ***	15.57
<i>N</i>		593		593
AIC		3 360		3 192
R_{adj}^2		0.56		-

Significance codes: 0.1 * 0.05 ** 0.01 ***

7 5.3. Results

8 The model results (Table 4) provide a range of interesting insights. First,
9 it was shown that economic and social activity were key drivers of demand
10 for free-floating bicycle-sharing in an area. Interestingly however, sports
11 facilities, cinemas or event halls did not have a significant effect. A potential
12 interpretation would be that the latter are usually visited as a couple or
13 group, for which free-floating e-bikes are a sub-optimal option.

1 As in earlier research, the bicycle network density had a positive impact.
2 Although the actual attractiveness of the bicycle mode mostly depended on
3 the infrastructure along the route, the model showed that a denser infras-
4 tructure increased bicycle trips. Neighborhoods with higher income levels
5 showed a higher demand, which makes sense given that the cost of the ser-
6 vice is relatively high compared to public transportation (which has zero
7 marginal cost for season ticket holders).

8 The model provided insight into the interdependence of free-floating bicycle-
9 sharing with public transportation services. All indicators related to public
10 transportation showed a positive effect, i.e. indicating that demand for free-
11 floating bicycle-sharing was higher in areas well-connected by public trans-
12 portation and those close to the central station and urban train stations.
13 This reflects earlier insights on car-sharing (Millard-Ball et al., 2005; Stillwa-
14 ter et al., 2009) indicating that shared mobility services rely on a functioning
15 public transportation service, which (1) provides mobility in case the shared
16 service is unavailable and (2) correlates with lower levels of car-ownership.
17 In contrast to Stillwater et al. (2009), heavy rail stations showed a partic-
18 ularly positive effect on bicycle-sharing demand, which may indicate that a
19 substantial share of customers use the scheme as an access or egress mode for
20 train journeys. The interpretation of *PTpassengers* was less immediate since
21 the demand matrix for private cars was not available. Hence, *PTpassengers*
22 may also be regarded as a proxy for general travel demand, such that the pa-
23 rameter estimate indicates that free-floating bicycle-sharing follows a similar
24 spatial distribution of demand as other modes, i.e. it does not only serve a
25 specific market niche.

26 It was interesting to see the high explanatory power of the model and the
27 fact that there was no clustering of unobserved effects. Given that demand
28 can be well explained by attributes available from open data, this model can
29 be used to predict demand and help to design service areas in other cities
30 too.

1 **6. Discussion**

2 The analysis conducted in this paper showed that e-bike-sharing effi-
3 ciently complements traditional public transportation. The range of typical
4 e-bike-sharing trips largely overlapped with traditional public transportation,
5 which indicated that e-bike-sharing caters to the same market segment with
6 respect to trip distances. During the night when traditional public trans-
7 portation service is not available or has a low service quality, e-bike-sharing
8 is, to some extent, used as a substitute. This is not surprising, as taxi prices
9 are comparatively high in Zürich (a 10 minute trip costs approximately CHF
10 30). This result may be of interest to public transportation providers that
11 seek to offer a cost efficient transportation service during the night, when de-
12 mand and operational costs of traditional public transportation do not justify
13 (frequent) service. As traditional public transportation is heavily subsidized
14 in the city of Zürich and by other cities, a case could be made to also subsi-
15 dize bicycle and e-bike-sharing systems that are open to the public (as these
16 systems are also a form of public transportation). Subsidizing traditional
17 public transportation but not e-bike-sharing distorts the market, which may
18 lead to a sub-optimal outcome.

19 The descriptive spatial analysis (rental start locations in the main busi-
20 ness district during the day), the times of the bookings (a distinct morning
21 and afternoon peak), and the regression model of daily bookings (a 37% re-
22 duction of trips on weekends) indicated that a major share of the demand
23 were commuting trips. Unsurprisingly, precipitation was also a factor affect-
24 ing demand of e-bike-sharing (-17% demand on days with precipitation). The
25 comparison of trip times of e-bike-sharing with alternative modes of trans-
26 portation showed that e-bikes were one of the fastest urban transportation
27 options. This is not surprising as Smide e-bikes reach speeds of 35 km/h
28 without much effort by the cyclist. This is a major advantage compared to
29 traditional bicycle-sharing systems, especially in countries and cities where
30 the value of travel time savings (VTTS) is high. High VTTS also justify
31 higher prices of e-bike-sharing compared to traditional bicycle-sharing.

32 Bicycle-sharing has seen considerable innovation since the “fourth gener-
33 ation” systems described by Shaheen et al. (2010). High smartphone pene-
34 tration, the capability to offer location-based services on a software level and
35 sophisticated applications have made efficient free-floating systems possible.
36 Bicycles can be located via smartphone and thus, docking stations and fixed
37 user interfaces have become optional. Users can be identified by being reg-

1 istered online, and locking and unlocking can also be done via smartphone.
2 E-bikes are changing the landscape of bicycle-sharing by allowing for greater
3 distances with more comfort for the cyclist. The combination of these factors
4 are likely to make bicycle-sharing much more competitive compared to earlier
5 systems, becoming serious competition for established public transportation
6 and taxi services. Furthermore, dynamic pricing (e.g. via bonus zones) can
7 be used to assist re-balancing, which lowers operational cost. The leap from
8 “fourth generation” systems is considerable and thus, these systems are seen
9 as “fifth generation” systems.

10 The results of the spatial regression model show that economic and social
11 activity were key drivers of demand for free-floating e-bike-sharing, which is
12 consistent with the descriptive analysis. Bicycle network density and pub-
13 lic transportation service quality have a positive impact on demand. This
14 indicates that e-bike-sharing systems complement traditional public trans-
15 portation. The results also have implications for investigations of potential
16 network effects for (electric) bicycle-sharing, as bicycle infrastructure and a
17 adequate public transportation service level may be necessary conditions for
18 the scalability of bicycle-sharing systems.

19 E-bike-sharing is a potential method for decreasing the energy consump-
20 tion of the transportation sector and increasing the quality of the public
21 transportation system as a whole. Regulatory agencies should strive not
22 to obstruct the development of such systems. This includes approving the
23 operation of e-bikes on existing bicycling facilities.

1 **Author contribution statement**

2 The authors confirm contribution to the paper as follows: study con-
3 ception and design: Sergio Guidon, Henrik Becker; data collection: Ho-
4 race Dediu; analysis and interpretation of results: Sergio Guidon, Henrik
5 Becker; draft manuscript preparation: Sergio Guidon, Henrik Becker, Kay
6 Axhausen. All authors reviewed the results and approved the final version
7 of the manuscript.

8 **7. References**

- 9 Anselin, L., Bera, A. K., Florax, R., Yoon, M. J., 1996. Simple diagnostic
10 tests for spatial dependence. *Regional Science and Urban Economics* 26,
11 77–104.
- 12 Becker, H., Ciari, F., Axhausen, K. W., 2017a. Comparing car-sharing
13 schemes in Switzerland: User groups and usage patterns. *Transportation*
14 *Research Part A* 97, 17–29.
- 15 Becker, H., Ciari, F., Axhausen, K. W., 2017b. Modelling free-floating car-
16 sharing use in Switzerland: A spatial regression and conditional logit ap-
17 proach. *Transportation Research Part C* 81, 286–299.
- 18 Box, G. E. P., Cox, D. R., 1964. An analysis of transformations. *Journal of*
19 *the Royal Statistical Society* 26 (2), 211–252.
- 20 Buck, D., Buehler, R., Happ, P., Rawls, B., Chung, P., Borecki, N., 2013. Are
21 Bikeshare Users Different from Regular Cyclists? A First Look at Short-
22 Term Users, Annual Members, and Area Cyclists in the Washington, D.C.,
23 Region. *Transportation Research Record* 2387, 112–119.
- 24 Cairns, S., Behrendt, F., Raffo, D., Beaumont, C., Kiefer, C., 2017.
25 Electrically-assisted bikes: Potential impacts on travel behaviour. *Trans-*
26 *portation Research Part A: Policy and Practice* 103, 327–342.
- 27 Campbell, A. A., Cherry, C. R., Ryerson, M. S., Yang, X., 2016. Factors
28 influencing the choice of shared bicycles and shared electric bikes in Beijing.
29 *Transportation Research Part C* 67, 399–414.

- 1 Campbell, K. B., Brakewood, C., 2017. Sharing riders: How bikesharing
2 impacts bus ridership in New York City. *Transportation Research Part A:
3 Policy and Practice* 100, 264–282.
- 4 Caulfield, B., O’Mahony, M., Brazil, W., Weldon, P., 2017. Examining usage
5 patterns of a bike-sharing scheme in a medium sized city. *Transportation
6 Research Part A: Policy and Practice* 100, 152–161.
- 7 Cliff, A. D., Ord, J. K., 1973. *Spatial processes: models & applications*. Pion,
8 London.
- 9 El-Assi, W., Mahmoud, M. S., Nurul Habib, K., 2017. Effects of built envi-
10 ronment and weather on bike sharing demand: a station level analysis of
11 commercial bike sharing in Toronto. *Transportation* 44, 589–613.
- 12 Faghih-Imani, A., Anowar, S., Miller, E. J., Eluru, N., 2017a. Hail a cab or
13 ride a bike? A travel time comparison of taxi and bicycle-sharing systems
14 in New York City. *Transportation Research Part A: Policy and Practice*
15 101, 11–21.
- 16 Faghih-Imani, A., Eluru, N., 2016. Incorporating the impact of spatio-
17 temporal interactions on bicycle sharing system demand: A case study of
18 New York CitiBike system. *Journal of Transport Geography* 54, 218–227.
- 19 Faghih-Imani, A., Hampshire, R., Marla, L., Eluru, N., 2017b. An empirical
20 analysis of bike sharing usage and rebalancing: Evidence from Barcelona
21 and Seville. *Transportation Research Part A* 97, 177–191.
- 22 Fishman, E., 2016. Bikeshare: A Review of Recent Literature. *Transport
23 Reviews* 36, 92–113.
- 24 Fishman, E., Washington, S., Haworth, N., 2013. Bike Share: A Synthesis of
25 the Literature. *Transport Reviews* 33 (2), 148–165.
- 26 Fishman, E., Washington, S., Haworth, N., 2014a. Bike share’s impact on
27 car use: Evidence from the United States, Great Britain, and Australia.
28 *Transportation Research Part D: Transport and Environment* 31, 13–20.
- 29 Fishman, E., Washington, S., Haworth, N., Mazzei, A., 2014b. Barriers to
30 bikesharing: an analysis from Melbourne and Brisbane. *Journal of Trans-
31 port Geography* 41, 325–337.

- 1 Fishman, E., Washington, S., Haworth, N., Watson, A., 2015. Factors influ-
2 encing bike share membership: An analysis of Melbourne and Brisbane.
3 *Transportation Research Part A* 71, 17–30.
- 4 Fyhri, A., Fearnley, N., 2015. Effects of e-bikes on bicycle use and mode
5 share. *Transportation Research Part D: Transport and Environment* 36,
6 45–52.
- 7 Médard de Chardon, C., Caruso, G., Thomas, I., 2017. Bicycle sharing sys-
8 tem ‘success’ determinants. *Transportation Research Part A: Policy and*
9 *Practice* 100, 202–214.
- 10 Millard-Ball, M., Murray, G., Ter Schure, J., Fox, C., Burkhardt, J., 2005.
11 Car-sharing: Where and how it Succeeds. Transit Cooperative Research
12 Program (TCRP) Report 108. Transportation Research Board, Washing-
13 ton.
- 14 Nair, R., Miller-Hooks, E., Hampshire, R. C., Busic, A., 2013. Large-Scale
15 Vehicle Sharing Systems: Analysis of Velib. *International Journal of Sus-*
16 *tainable Transportation* 7, 85–106.
- 17 Noland, R. B., Smart, M. J., Guo, Z., 2016. Bikeshare trip generation in New
18 York City. *Transportation Research Part A* 94, 164–181.
- 19 Rixey, R. A., 2013. Station-Level Forecasting of Bikesharing Ridership.
20 *Transportation Research Record* 2387, 46–55.
- 21 Shaheen, S., Guzman, S., Zhang, H., 2010. Bikesharing in Europe, the Ameri-
22 cas, and Asia. *Transportation Research Record: Journal of the Transporta-*
23 *tion Research Board* 2143, 159–167.
- 24 Stillwater, T., Mokhtarian, P. L., Shaheen, S. A., 2009. Carsharing and the
25 Built Environment: Geographic Information System-Based Study of One
26 U.S. Operator. *Transportation Research Record* 2110, 27–34.
- 27 Swiss Federal Statistical Office (BFS), 2016. Statistik der Bevölkerung und
28 der Haushalte (STATPOP). Tech. rep., Swiss Federal Statistical Office
29 (BFS), Neuchatel.
- 30 Swiss Federal Statistical Office (BFS), 2017a. Mobilität in der Schweiz -
31 Ergebnisse des Mikrozensus Mobilität und Verkehr 2015. Tech. rep., Swiss
32 Federal Statistical Office (BFS), Neuchatel.

- 1 Swiss Federal Statistical Office (BFS), 2017b. Statistik der Un-
2 ternehmensstruktur (STATENT). Tech. rep., Swiss Federal Statistical Of-
3 fice (BFS), Neuchatel.
- 4 Wergin, J., Buehler, R., 2017. Where do Bikeshare Bikes Actually Go? Anal-
5 ysis of Capital Bikeshare Trips with GPS Data. *Transportation Research*
6 *Record* 2662, 12–21.
- 7 Yang, X. H., Cheng, Z., Chen, G., Wang, L., Ruan, Z. Y., Zheng, Y. J.,
8 2018. The impact of a public bicycle-sharing system on urban public
9 transport networks. *Transportation Research Part A: Policy and Practice*
10 107 (September 2016), 246–256.