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Author(s):
Guidon, Sergio; Becker, Henrik; Dediu, Horace; Axhausen, Kay W.

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Electric bicycle-sharing: a new competitor in the urban transportation market? An empirical analysis of transaction data

Sergio Guidon[a,b], Henrik Becker[b], Horace Dediu[c], Kay W. Axhausen[a,b]

[a]*Institute of Science, Technology and Policy (ISTP), ETH Zürich, Universitätstrasse 41, 8092 Zürich, Switzerland*
[b]*Institute for Transport Planning and Systems (IVT), ETH Zürich, Stefano-Franscini-Platz 5, 8093 Zürich, Switzerland*
[c]*Smide, Zentralstrasse 118, 8003 Zürich, Switzerland*

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). Spatiotemperal demand patters are not symmetric, making relocations necessary (Nair et al., 2013). In particular, stations at elevated locations are unattractive destinations (Faghih-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).

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

2. Background

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

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

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

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

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

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

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

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

3. Descriptive Analysis

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

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

3.1. Data Sources and Regional Context

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

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

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

area. The Zürich metropolitan area is Switzerland's economic center, where approximately 200,000 people commute to and more than half use public transportation. Zürich is located in the pre-Alps and exhibits a maximum elevation difference of ca. 480 m within its municipal area. Public transportation service quality is considered very high, with 4.7 public transportation stops per square kilometre and a regulation that all residents should be able to reach a public transportation stop within 400 meters, the city's goal is 300 meters. (For general information about the city refer to `https://www.stadt-zuerich.ch/`, last accessed: July 2018.) In 2017, three bicycle-sharing systems were available in Zürich: O-Bike (meanwhile discontinued), a station-based system operated by the city of Zürich (both without e-bikes), and Smide.

3.2. Trip Data Overview

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

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

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

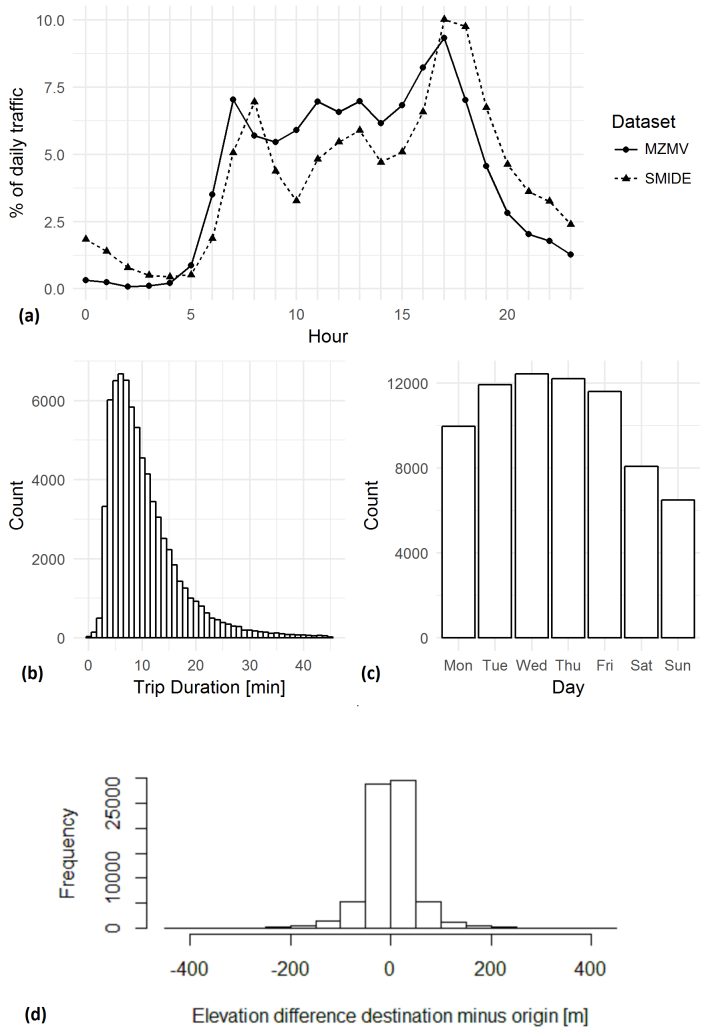

FIGURE 1: Smide trip data overview: (a) % of daily traffic by hour (household travel survey (MZMV) vs. Smide), (b) trip duration distribution, (c) trip frequencies by day of the week, (d) elevation difference distribution (desination minus origin).

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

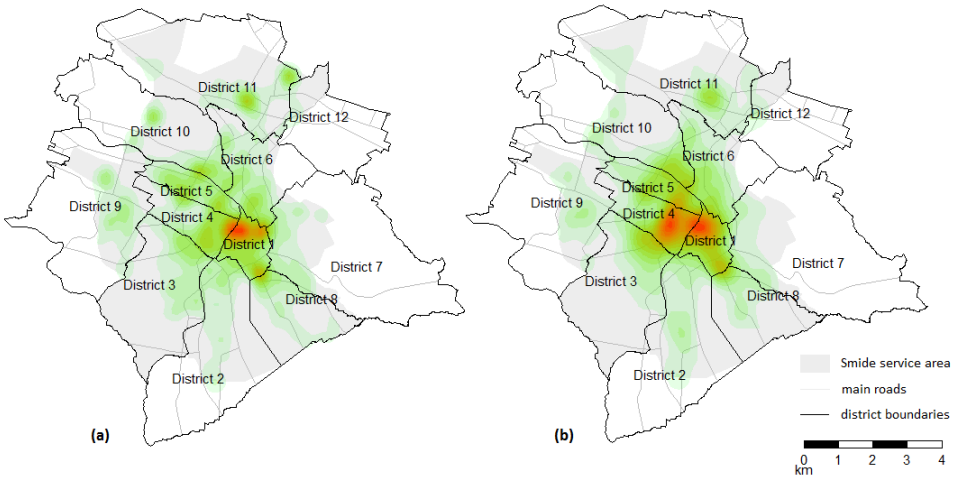

FIGURE 2: (a) Spatial distribution of rental start locations (all bookings), and (b) late night bookings (10 pm until 6 am).

3.3. Market Segmentation: Analysis of Trip Distributions

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

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

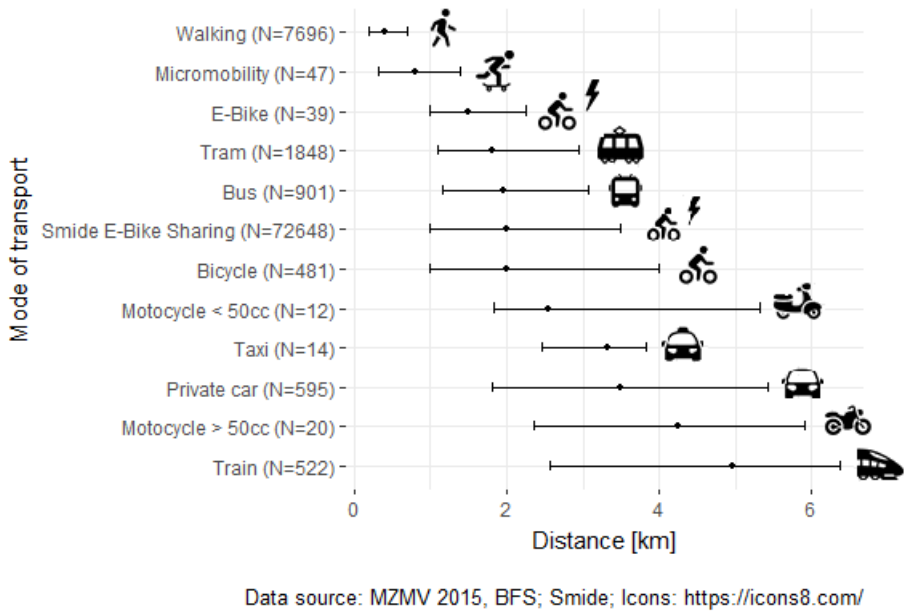

FIGURE 3: Distance ranges in the urban passenger transportation market: median, and the upper/lower quartiles.

Although not the focus of this paper, it is interesting to note that micromobility (skateboards, kickboards etc.) efficiently fills the gap between walking and cycling.

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

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

would have been faster at the median. 18.2% of transit trips involved at least one transfer, and in 18.1% of the cases the trip time corresponded to the walking time, as public transportation was not a feasible option. For transit, walking time was included, while for taxi and Smide, the time corresponded to the actual trip time. The total trip time of Smide would also include walking time to the nearest e-bike. For taxis, the total trip time would also include waiting time. For transit, transfers constitute a disutility and the time between desired departure time and actual departure time was not considered. Therefore, the times in Table 1 are generally rather optimistic. Furthermore, it is likely that Smide was only chosen if an e-bike was close to the desired origin of the trip and therefore, the data is subject to an unknown amount of censored demand. Thus, as a comparison, 12,215 trips from the Swiss household travel survey (MZMV) were also analyzed (see Table 1 "MZMV data"). The Google Directions API was used to generate proxy travel times for Smide. For MZMV trips in the city of Zürich, Smide was the fastest mode at the median, and at the first quartile. At the mean and at higher quantiles, a private car or taxi was faster. This can be explained by the fact that an average trip from the Swiss household travel survey is only 1.5 km (compared to the average Smide trip distance of 2.5 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.

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

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

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

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

	Negative binomial model		
	Coef.		SE
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 ***

5. External Drivers of Demand

5.1. Data

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

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

an urban rail station (*urbanRail200*) and 500 m to the main train station (*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			

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

5.2. Methodology

As shown in Table 3, the response variable (number of rentals) does not follow a normal distribution. Hence, a count-data model (e.g. negative binomial) must be used or the response variable needs to be transformed to allow application of linear regression. Since Figure 4 already indicates a spatial structure in the data, the latter option was chosen (spatial models for count data are still rare in the literature). Thus, a Box-Cox transformation (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^2_{adj} 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 ($\mathrm{LM}_{lag} = 18.0$, df= 1, $p < 2.2 \cdot 10^{-5}$). However, spatial autocorrelation

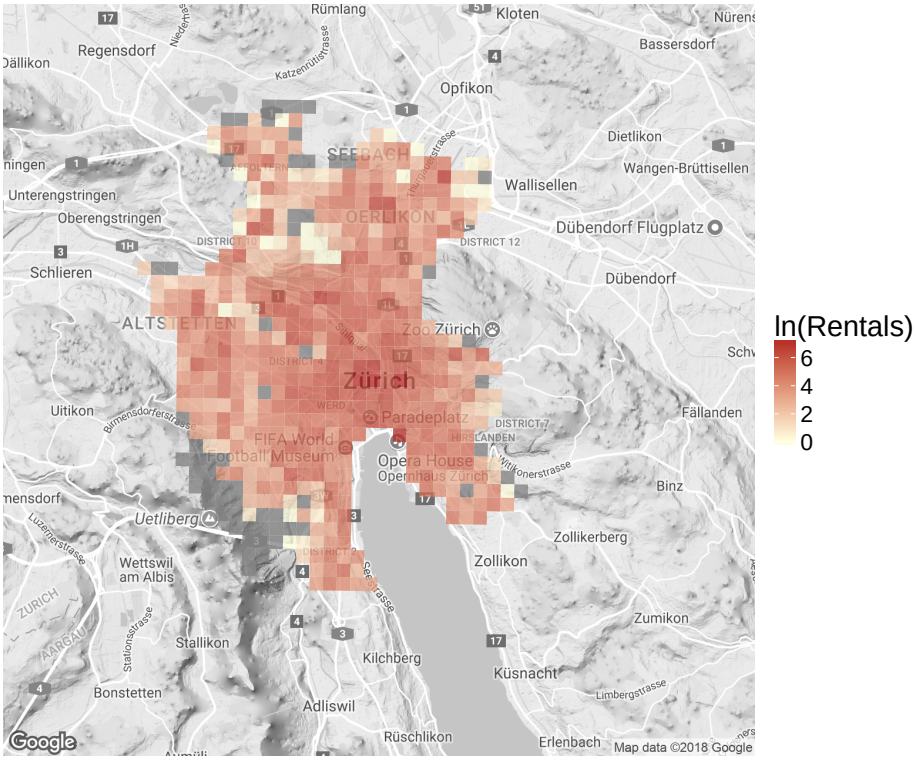

FIGURE 4: Number of reservations (logarithm) per raster cell from yellow (low) to dark red (high). Zones with no observations are given in grey.

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

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

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

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

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

	simple linear model			spatial lag model		
	Coef.		t	Coef.		t
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
N	593			593		
AIC	3 360			3 192		
R^2_{adj}	0.56			-		

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

5.3. Results

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

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

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

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

6. Discussion

The analysis conducted in this paper showed that e-bike-sharing efficiently complements traditional public transportation. The range of typical e-bike-sharing trips largely overlapped with traditional public transportation, which indicated that e-bike-sharing caters to the same market segment with respect to trip distances. During the night when traditional public transportation service is not available or has a low service quality, e-bike-sharing is, to some extent, used as a substitute. This is not surprising, as taxi prices are comparatively high in Zürich (a 10 minute trip costs approximately CHF 30). This result may be of interest to public transportation providers that seek to offer a cost efficient transportation service during the night, when demand and operational costs of traditional public transportation do not justify (frequent) service. As traditional public transportation is heavily subsidized in the city of Zürich and by other cities, a case could be made to also subsidize bicycle and e-bike-sharing systems that are open to the public (as these systems are also a form of public transportation). Subsidizing traditional public transportation but not e-bike-sharing distorts the market, which may lead to a sub-optimal outcome.

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

Bicycle-sharing has seen considerable innovation since the "fourth generation" systems described by Shaheen et al. (2010). High smartphone penetration, the capability to offer location-based services on a software level and sophisticated applications have made efficient free-floating systems possible. Bicycles can be located via smartphone and thus, docking stations and fixed user interfaces have become optional. Users can be identified by being reg-

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

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

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

Author contribution statement

The authors confirm contribution to the paper as follows: study conception and design: Sergio Guidon, Henrik Becker; data collection: Horace Dediu; analysis and interpretation of results: Sergio Guidon, Henrik Becker; draft manuscript preparation: Sergio Guidon, Henrik Becker, Kay Axhausen. All authors reviewed the results and approved the final version of the manuscript.

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