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

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.

In this paper, 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 are 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 is 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 differences in the service compared to traditional bicycle-sharing, 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

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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 operational issues 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, putting into practice 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 (i.e. no full stations at the destination and a shorter distance to the actual destination of the journey), 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), finding that 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. Two statistical models were used to analyze the data: a) a negative binomial model to investigate the effects of weather and day of the week on daily bookings and b) a spatial regression model to connect the number of bookings to spatial attributes, i.e. population and work place density, infrastructure, public transportation availability and income. The booking data was complemented with data from the Swiss household travel survey in order to discuss the e-bike-sharing market and the competitive position of e-bike-sharing compared to other modes of transportation. The effect of e-bike-sharing on the overall transportation system was also discussed. 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 schemes 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 traveled 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 competitive in terms of speed 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 (1.86 miles). 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 renders it 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 (cf. Becker et al. (2017a)). As a result, mode substitution and impact on vehicle-miles travelled may be different.

Although the literature on e-bike-sharing is sparse, there are a number of findings on the effect of e-bikes on travel behavior. 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. De Kruijf et al. (2018) report the results of a monetary incentive program to stimulate the use of e-bikes in the Netherlands with the goal to support the shift from car commuting to e-cycling. The authors found that half of the e-bike trips substituted car trips, while the other half substituted conventional cycling trips. The high substitution rate of private car trips in the Brighton trial and in the study in the Netherlands 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). De Kruijf et al. (2018) also find that e-bikes are used for longer distances compared to traditional bicycles. The shift from car commuting to e-cycling was also sensitive to socio-demographic and household characteristics.

For e-bike-sharing, 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. Regional Context and Data Source

3.1. Smide E-Bike-Sharing

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 operations 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 (approximately 28 mph), however, the speed was reduced to 35 km/h (approximately 21.7 mph) 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. 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 five 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 battery changes are done with a cargo e-bike.

3.2. E-Bike-Sharing Dataset and the Swiss Household Travel Survey

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 of 2015, "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).

3.3. Regional Context

Zürich is a medium-sized city in Switzerland (Central Europe) 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 Prealps 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 (0.25 miles) from their home location, the city's goal is 300 meters (0.19 miles). (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 (aimed at daily rentals for tourists and without e-bikes), and Smide.

3.4. Trip Times and Elevation Differences

For the descriptive analysis, trip times for potential alternative modes of transportation were estimated using the Google Directions API (`https://developers.google.com/maps/documentation/directions`, last accessed: July 2018). The trip times for cycling from the Google Directions API turned out to be a good proxy for e-bike-sharing trips (at the mean, the ratio of Google trip times to Smide trip times was 0.97). Elevation differences along the routes were determined with the Google Elevation API (`https://developers.google.com/maps/documentation/elevation/`, last accessed: July 2018).

3.5. Weather Data

In order to analyze variations of the the number of daily bookings, the booking data was complemented with weather data. The weather data was obtained from the Swiss Federal Office of Meteorology and Climatology for one representative station in the city of Zürich (i.e. the "Fluntern" station). (Weather data for Switzerland can be found here: `https://www.meteoschweiz.admin.ch/`, last accessed: July 2018.)

3.6. Spatial Analysis: Additional Sources and Transformations

To study the effect of spatial characteristics on 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 corresponds to the maximum distance travellers are 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 is available at hectare resolution; for the raster cells, the corresponding averages were used. Service levels for public transportation is defined by the Swiss standard SN-640290 (*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) is available from the same source, but only 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) are 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 individuals was used (the actual gross income usually is substantially higher). From the same source, the locations of all registered bars and restaurants were obtained and aggregated to the raster cells (*gastronomy* gives the count per zone). Further leisure facilities (such as sports facilities or cinemas) are also available, but their effect was neither significant nor substantial in the later modelling process. A shapefile with the city's bicycle infrastructure was also 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 1.

Figure 1 shows the spatial distribution of trip start locations. It indicates 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.

TABLE 1: 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
number of rentals per zone (during study period)						
popSize	0.0	0.008	0.052	0.073	0.113	0.394
population size per zone (in thousands)						
workPlace	0.0	0.003	0.006	0.085	0.470	2.012
number of work places per zone (in thousands)						
income	30.1	38.5	42.5	43.2	48.4	60.0
median taxable annual income of individuals per zone (in 1 000 CHF)						
gastronomy	0.0	0.0	1.0	3.5	3.0	71
number of registered bars and restaurants per zone						
bikeInfra	0.0	0.8	1.3	1.3	1.7	3.5
total length of dedicated bicycle infrastructure per zone (in km)						
PTpassengers	0.0	0.0	0.0	3.6	4.9	96.9
number of passengers boarding or alighting a bus or tram during workdays						
GAperInh	0.0	2.5	2.7	3.5	4.4	7.8
percentage of holders of a national season ticket for public transport						
highPTlevel			22% of the zones			
public transport service level A (according to standard SN 640 290						
urbanRail200			18% of the zones			
closer than 200 m to an urban rail station						
HB500			3% of the zones			
closer than 500 m to main train station						

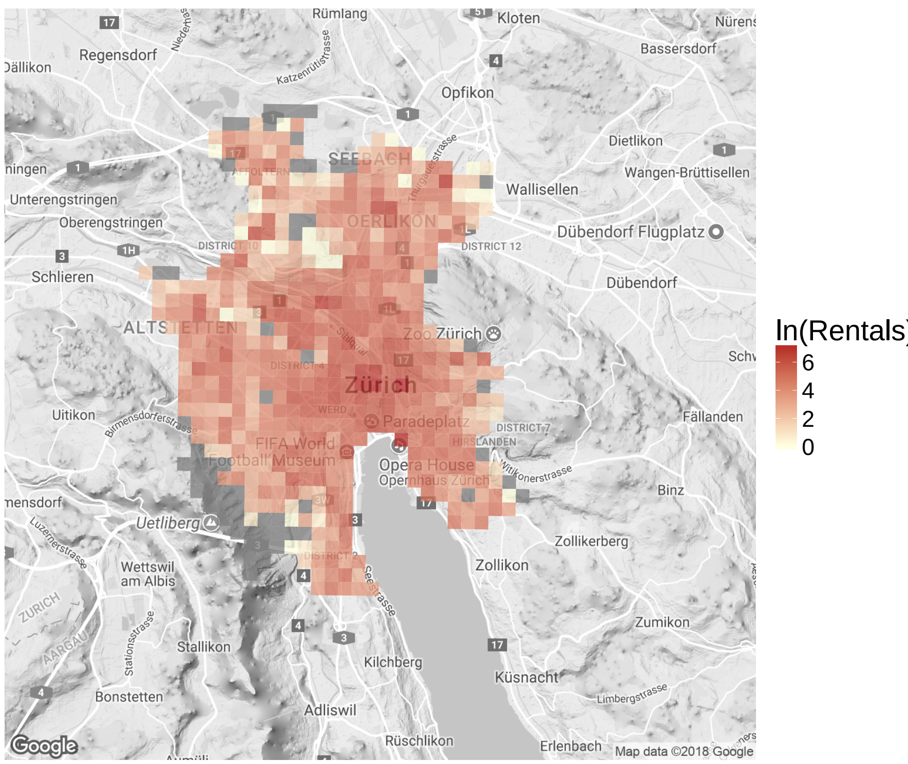

FIGURE 1: Number of reservations (logarithm) per raster cell from yellow (low) to dark red (high). Zones with no observations are given in grey.

4. Descriptive Analysis

This section presents descriptive statistics of the booking data and shows the potential market niche for e-bike-sharing with respect to trip distance.

4.1. Trip Data Overview

Figure 2 presents 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 (1.55 miles) 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 higher demand than weekend days indicate that a significant share of the demand is 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 bulk of the demand therefore arises during times of the day when public transportation service quality is 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, traditional public transportation would, therefore, not be an alternative to Smide.

A histogram of the number of bookings per month is shown in Figure 3. The system exhibited strong growth between April and July 2017. The relative share of bookings by time of day remained stable.

One advantage of e-bikes is the lower sensitivity towards terrain elevations. Figure 2 d) shows the distribution of elevation differences between destinations and origins. The figure indicates that trips were not primarily up- or downhill. Thus, e-bikes were used independent of elevation.

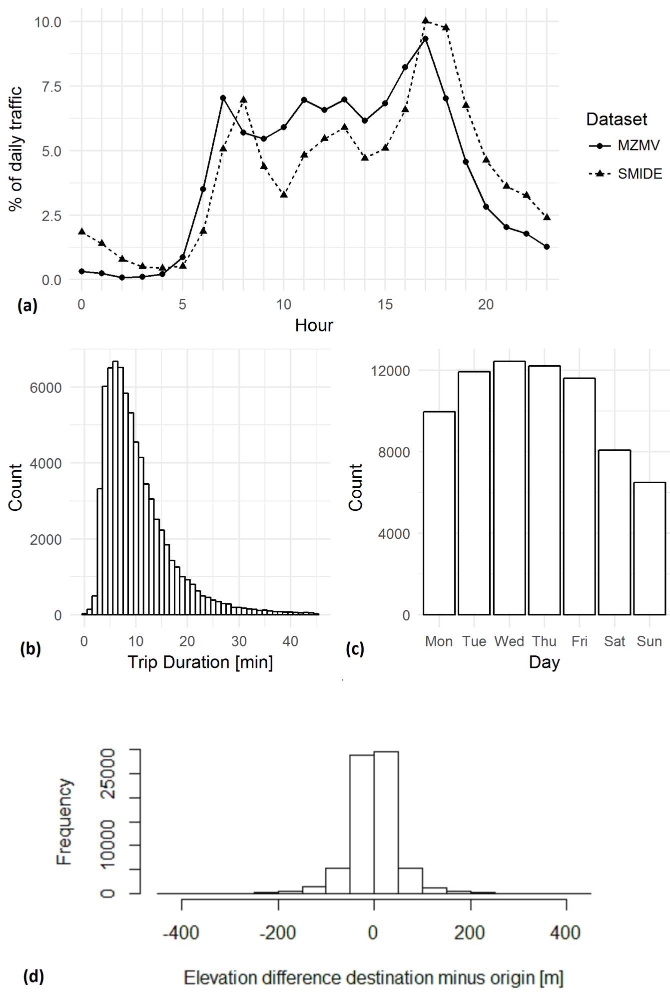

FIGURE 2: Smide trip data overview: (a) % of daily traffic by hour (household travel survey (MZMV) vs. Smide), (b) trip duration distribution, (c) trip frequencies by day of the week, (d) elevation difference distribution (desination minus origin).

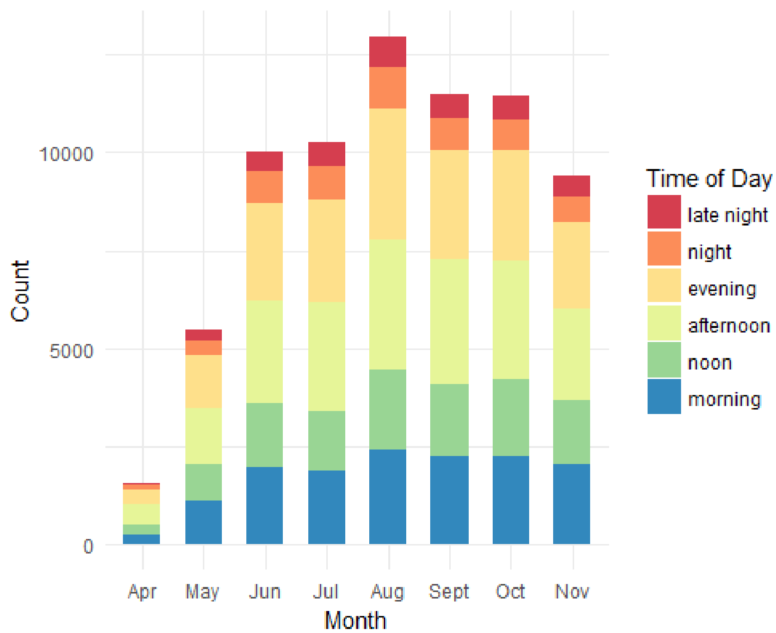

FIGURE 3: Histogram of monthly bookings.

Figure 4 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.

4.2. 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 5 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.

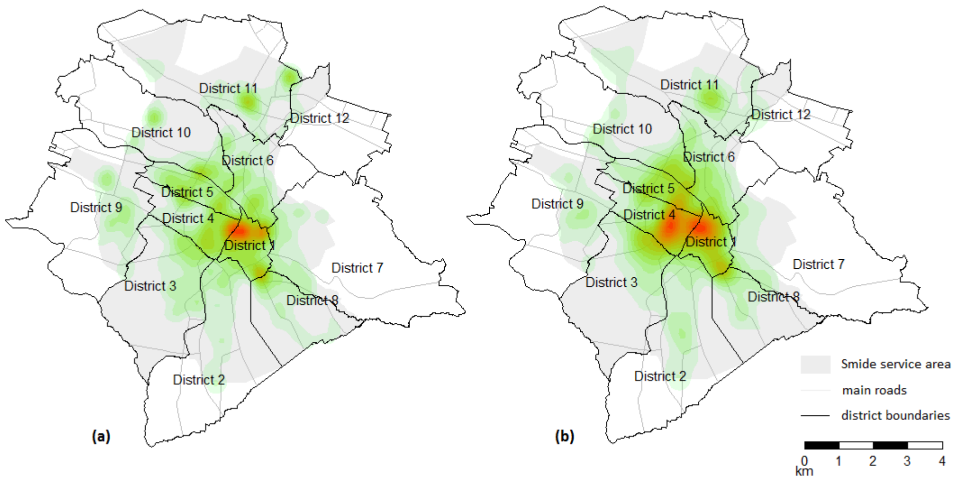

FIGURE 4: (a) Spatial distribution of rental start locations (all bookings), and (b) late night bookings (10 pm until 6 am).

E-bikes and e-bike-sharing trips are in the same distance range as traditional public transportation (buses and trams), cycling with a private bicycle, and small motorbikes. Taxi trips are longer than e-bike-sharing trips at the median, but the distance range of taxi trips is also not atypical for e-bike-sharing (despite the low sample size, the distance distribution of Zurich taxi trips was found consistent with the other large cities in Switzerland). The comparison of modes indicates that e-bike-sharing may be able to substitute a wide range of trips of other modes of transportation.

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.

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

Smide e-bike-sharing trip times were compared to the alternatives taxi, transit and walking to show the competitiveness of e-bike-sharing in terms of speed. Trip times were obtained with the Google Directions API. The comparison of trip times for the Smide data is shown in Table 2. 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 public transportation was not available. For transit, walking time was included in Table 2, while for taxi and Smide,

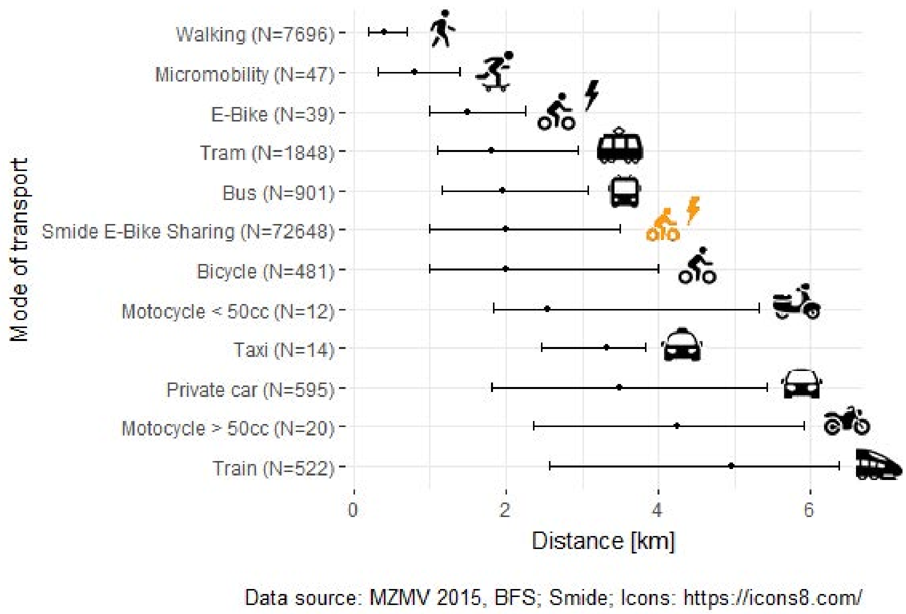

FIGURE 5: Distance ranges in the urban passenger transportation market: median, and the upper/lower quartiles.

the time corresponded to the in-vehicle time. Thus, the reported times do not include a) waiting time for taxis, b) searching time for e-bikes and c) walking time to the closest e-bike. The time between desired departure time and actual departure time was also not considered. Thus, the travel times in Table 2 are generally rather optimistic for all modes.

It is also 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 2 "MZMV data"). The Google Directions API was used to generate proxy travel times for Smide (Google bicycle routing) and the alternative modes of transportation. For MZMV trips in the city of Zürich, Smide was the fastest mode at the first quartile, and at the median. 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 or 0.93 miles (compared to the average Smide trip distance of 2.5 km or 1.55 miles) and the car plays out its strengths at longer trip distances.

TABLE 2: 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. The the mode with the shortest trip time is highlighted.

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.

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

5.1. Methodology

A negative binomial regression model was estimated to analyze the effect of weather and day of the week on the number of daily bookings (dependent variable). In order to differentiate between weekend and working days, a dummy for the weekend days was 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 (see Figure 3). During this period a mean of 364 bookings per day (with a median 356) were made.

5.2. Results

Temperature, precipitation, and the weekend dummy had highly significant and substantial effects on the number of bookings (see Table 3). Solar radiation was significant, but not substantial. 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 3: Regression models for the number of daily bookings: the effect of temperature, solar radiation, precipitation and weekend. Coefficients and incidence rate rations (IRR).

	Negative binomial model			
	Coef.		SE	IRR
number of bookings				
temperature	0.01	**	0.01	0.01
solar radiation	0.00	*	0.00	0.00
precipitation dummy	-0.18	***	0.03	-0.17
weekend dummy	-0.46	***	0.04	-0.37
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 ***				

6. The Effect of Spatial Characteristics on Demand

6.1. Methodology

The effect of spatial characteristics on demand was investigated with a spatial regression model. However, the summary of the variable in Table 1 indicates that 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 1 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 of the disturbances was weak ($\mathrm{LM}_{err} = 6.9$, 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 buffer 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). An example for the spatial weights is given in Figure 6.

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 ($\mathrm{LM}_{err} = 0.02$, $p = 0.9$).

6.2. 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

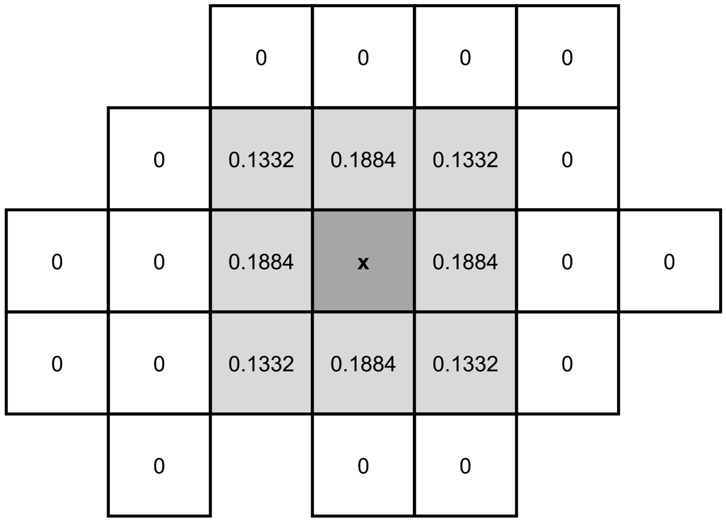

FIGURE 6: Example for spatial weights used in the SAR model.

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 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 partic-

TABLE 4: Regression models for free-floating bicycle-sharing demand. The number of departures was Box-Cox transformed before estimation.

	simple linear model			spatial lag model		
	Coef.		t	Coef.		z
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 (Number of zones)	593			593		
AIC	3 360			3 192		
R^2_{adj}	0.56			-		

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

ularly 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.

To complement the above findings, disaggregated models were estimated for different start times and weather conditions. Table 5 presents a selection of these models. While the general trends outlined above still hold for the disaggregated models, there are a few noteworthy nuances: as expected, work places do not generate e-bike-share departures during morning times and weekends. Yet, they increase demand in rainy conditions. In turn,

TABLE 5: Regression models for free-floating bicycle-sharing demand - selected cases.

	Weekday Coef.	Weekend Coef.	Precipitation Coef.	Morning[a] Coef.	Afternoon[b] Coef.	Night[c] Coef.
number of departures						
popSize (in thousands)	11.14 ***	10.07 ***	6.35 ***	10.41 ***	7.34 ***	7.60 ***
workPlace (in thousands)	1.48 ***	0.72	0.95 **	0.68	1.41 ***	0.81 **
highPTlevel (dummy)	0.92 ***	0.88 ***	0.81 ***	0.50 *	0.80 ***	0.87 ***
PTpassengers (count)	0.13 ***	0.10 ***	0.07 ***	0.10 ***	0.10 ***	0.06 ***
income (in 1000 CHF)	0.06 **	0.04 ***	0.04 ***	0.04 ***	0.04 **	0.03 **
gastronomy (count)	0.03	0.05 ***	0.03 *	0.00	0.02	0.05 ***
bikeInfra (km)	0.78 ***	0.66 ***	0.40 **	0.47 **	0.61 ***	0.59 ***
urbanRail200 (dummy)	0.73 **	0.42	0.39 *	0.50 *	0.44 *	0.35
HB500 (dummy)	1.29	1.18 *	0.55	0.77	1.02	0.60
GAperInh (percent)	-0.06	0.00	-0.02	-0.01	-0.05	0.01
(Intercept)	-3.03 ***	-2.67 ***	-2.79 ***	-2.89 ***	-2.38 ***	-3.00 ***
λ	0.62 ***	0.55 ***	0.57 ***	0.62 ***	0.63 ***	0.49 ***
N (Number of zones)	593	593	593	593	593	593
n (Number of bookings)	58 083	14 565	5 025	14 285	19 174	5 448
AIC	3 025	2 758	2 594	2 808	2 759	2 549

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

[a] morning: between 7 am and 11 am; [b] afternoon: between 2 pm and 6 pm; [c] night: between 10 pm and 1 am

restaurants and bars generate demand primarily during weekends and at night. Most interestingly, the main train station has a significantly positive effect only during weekends, while at all other times, demand is higher close to urban rail stations.

It is also interesting to note the high explanatory power of the models 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.

7. Limitations

The results obtained in the analysis provide interesting insights, but due to limited data availability the analysis also exhibits some limitations. The main limitation of the descriptive analysis is that the data did not allow for a comparison of total journey times. For Smide, walking time to the nearest e-bike could be considered in future analyses if the data is available. One way to approximate walking and searching time would be to analyze the time difference between opening the application and the time of the booking in detail. Waiting time for taxis was also not included in the comparison and thus, the fairness of the comparison between taxis and e-bikes hinges on the actual difference between waiting time for taxis and searching and walking time for e-bikes.

The data from Smide is from 2017, while the data of the household travel survey is from 2015. However, no substantial changes in travel patterns have been observed within these two years.

The Smide booking data did also not contain detailed information about the users such as sex, season ticket availability and other socio-demographic and household characteristic. For future studies, it would be interesting to combine booking data with survey data to investigate the influence of these variables on usage patterns.

The negative binomial model of the effect of weather and day of the week on daily bookings was based on data from July to November, which excludes the coldest time of the year in Zurich (which is from December until February). This was due to the strong growth of the system. The effect of temperature may be stronger if it falls below a certain threshold (which could occur in the colder months of the year). One way to use the full dataset could have been to account for the growth of the system by using an auto-regressive moving average (ARMA) model.

8. Discussion

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 (21.7 mph) 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 for e-bike-sharing compared to traditional bicycle-sharing.

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). Furthermore, Smide likely also complements traditional public transportation for origin-destination pairs with inefficient public transportation supply. 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.

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.

The analysis conducted in this paper also showed that e-bike-sharing is able to complement traditional public transportation. In an urban setting, the range of typical e-bike-sharing trips largely overlaps with traditional public transportation, which indicates that e-bike-sharing caters to the same market segment with respect to trip distances.

9. Conclusion

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 registered 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 competition 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 can be seen as "fifth generation" systems.

In terms of generalizability, the case of Zurich may be special insofar as the wages are comparatively high (the median monthly gross salary is approximately CHF 7700, which corresponded to $7700 US in May 2018). In addition, public transportation quality is considered very high, while bicycling infrastructure is comparable to other European cities of similar size. Due to its geographic location in the Prealps, terrain elevation differences may more pronounced than in other cities. The comparatively high income combined with terrain elevation differences could make Zurich particularly suitable for a high-end e-bike-sharing system such as Smide. However, high wages also translate to higher operational costs and a similar system would also be possible with cheaper e-bikes. Furthermore, the general trend in the e-bike market goes towards lower prices at the same level of quality. Thus, a similar system would be thinkable in many cities in the developed world.

E-bike-sharing may potentially be an environmentally efficient way to cater to spatially dispersed transportation demand for a large range of trips distances in urban areas. As a novel form of public transportation, e-bike-sharing efficiently complements traditional public transportation and taxi services at comparable speeds and can be an alternative when traditional urban public transportation systems are too cost intensive.

Author contribution statement

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

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