Shared micromobility in Zurich, Switzerland: Analysing usage, competition and mode choice

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Abstract

Shared micromobility services (e-scooters, bicycles, e-bikes) have rapidly gained popularity in the past few years, yet little is known about their use. While most previous studies have analysed datasets from single providers, only few comparative studies between two or more modes exist and none so-far have analysed competition and mode choice at a high spatiotemporal resolution. To this end, we analysed a large and dense dataset containing ~56M vehicle locations and ~46K trips of 5 different shared micromobility providers for two weeks in January 2020 in Zurich, Switzerland. Bivariate relationships and a MNL mode choice model exhibit 3 main results: (1) docked modes (bike and e-bike) exhibit a clear commuting pattern (morning and evening peak), while dockless e-scooters exhibit the opposite pattern (i.e., morning and evening trough and night peak); (2) dockless e-scooters are preferred for very short trips, docked bikes for medium trips in even terrain or downhill, and e-bikes for longer uphill trips; (3) choice probability increases with vehicle density and battery charge particularly for dockless modes, however there is first evidence of a plateau (i.e., decreasing marginal utility gains up to a level of indifference in choice behaviour).

Keywords: micromobility, competition, mode choice

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1. Introduction

Shared micromobility services (dockless e-scooters, dockless and docked bikes and e-bikes) have rapidly gained popularity in the past few years. Their appearance has been welcomed by many as novel, fun, spatially efficient and sustainable new additions to the transport landscape. Others take a more critical stance questioning sustainability, safety and equity (particularly in the case of e-scooters).

While many speculate about their impact, research to guide policymaking is still in its infancy (cf. recent Call for Papers, Transportation Research Part D): How are different shared micromobility services being used? How does usage compare between different micromobility services across space and time? How do users choose between different (competing) micromobility services, and between them and other more established means of transport such as public transport and walking? Providing rigorous answers to these questions can support transport planning and regulation in various ways, such as clarifying their potential to substitute car trips, alleviate roads during the commute and reduce the footprint of the transport sector.

The existing body of knowledge strongly varies by mode. While shared docked bikes have a relatively long (research) history (at least in comparison with other shared micromobility modes) (e.g., Bachand-Marleau et al., 2012; Fishman et al., 2013; Shaheen et al., 2011), the literature on dockless (e-)bikes is much younger and already limited in scope (e.g., Campbell et al., 2016; Guidon et al., 2019; He et al., 2019; Shen et al., 2018). Dockless e-scooters are the latest addition to the micromobility mix and only recently have seen first peer-reviewed publications (e.g., Bai and Jiao, 2020; Mathew et al., 2019; McKenzie, 2019; Noland, 2019; Younes et al., 2020). Most previous studies employ datasets of a single shared micromobility service and only few comparative studies exist (e.g., Campbell et al., 2016; Lazarus et al., 2020; McKenzie, 2019; Younes et al., 2020). In particular, competition and mode choice *between* shared micromobility services has not been studies yet, however this is an increasingly relevant topic with the steady rise of new providers.

We address this gap by analysing a scraped dataset containing over 56M vehicle locations and over 46K micromobility trips of 5 micromobility providers of docked and dockless e-bikes, bikes and e-scooters for two weeks in January 2020 in Zurich, Switzerland. We describe in detail how to extract trips from scraped vehicle locations and validate scraped trips against real booking data obtained for 3 of the 5 providers. We proceed by analysing usage and identifying similarities and differences between the different providers and modes. Finally, we define competition situations by identifying all available micromobility alternatives for each trip using real-time spatiotemporal vehicle location information and estimate a multinomial logit model to investigate mode choice.

Our contributions are twofold. First, we compare micromobility usage patterns using a single large and dense dataset of quality near to real booking data for five different micromobility providers and modes. This allows to detect subtle differences in usage that allows comprehensive lessons and might otherwise be attributed to location biases. Second, we estimate a first mode choice model for micromobility. To our knowledge, this has not been done before and offers relevant lessons for policy, research and practice. Policymakers can learn about mode choice at different times of day to adjust regulation on vehicle licensing and parking in critical infrastructure zones. Researchers can use our results to update micromobility mode choice in simulations to forecast system effects in cities where micromobility (at scale) has not been introduced yet. Prospective providers can employ our results to optimize their repositioning (e.g., by time of day, elevation, battery charge) and evaluate their competitive position in new micromobility markets.

The remainder of this article is organized in 5 sections. We first review the literature on micromobility with a particular focus on usage and mode choice. We then introduce our dataset both conceptually and descriptively, and introduce the methods used to subsequently analyse bivariate and multivariate relationships between mode choice and trip / provider attributes. We present and discuss our results, and close with a summary and discussion of the implications for research, practice and policy.

2. Literature Review

The number and variety of shared micromobility services has steadily increased in recent years and now includes many different modes such as docked bikes / e-bikes, dockless bikes / e-bikes and dockless e-scooters. Research on shared micromobility can be categorized mainly into supply- and demand-side matters, of which the latter is more relevant to the topic of this paper. Demand-side research on shared micromobility is usually focused on questions such as how and why specific services are used. Demand-side research can be further categorized by types of factors that influence demand such as internal (i.e., user socio-demographics), external (e.g., built environment, geography, weather) and trip-related (destinations, distance, time of day). Again, the latter two are most relevant to the topic of this paper and thus focus of this literature review.

Research analysing external and trip-related factors that influence demand for shared micromobility services began with studies on station-based bikesharing (which we refer to as “docked” in this paper to contrast the “dockless” alternatives) (e.g., Shaheen et al., 2011). A number of factors have since been identified to influence demand for shared bikes, such as population density, workplace density, social and leisure centre density, public transport density, elevation difference and weather (Bachand-Marleau et al., 2012; Campbell and Brakewood, 2017; Fishman et al., 2013; Fishman et al., 2014; Murphy and Usher, 2015; Noland et al., 2016; Ricci, 2015; Shaheen et al., 2011). The magnitude of these factors generally varies with time (time of day, day of week, and month of the year). For example, while the effect of workplaces is usually found to be positive on weekdays, it is found to be negative during weekends. In conjunction with often observed morning and evening demand peaks, this suggests that important driver of demand is the commute (e.g., McKenzie, 2019). Adverse weather (precipitation, wind) usually has a negative influence on use, while agreeable weather conditions are associated with higher levels of usage. Finally, while several positive factors have been associated with docked bikes (e.g., generally more cycling and active travel, health-related benefits, low emissions), they have been found to primarily substitute walking and public transport trips instead of the private car (Bachand-Marleau et al., 2012; Campbell and Brakewood, 2017; Fishman et al., 2013; Fishman et al., 2014; Murphy and Usher, 2015; Shaheen et al., 2011). Recently, dockless (e-)bikesharing systems have gained substantial scholastic attention. While external factors have generally been found to be similar to docked bikesharing, trips tend to be longer (i.e., between 2 and 3 km) and elevation naturally does not appear to influence systems with electric support (Campbell et al., 2016; Guidon et al., 2019; Guidon et al., 2020; He et al., 2019; MacArthur et al., 2014; Shen et al., 2018).

Shared e-scooters are a relatively recent addition to the shared micromobility mix, thus only few peer-reviewed academic studies have analysed external factors influencing demand yet. Most studies have been conducted using the publicly available booking datasets from Louisville (KY) (Noland, 2019; Reck et al., 2020), Austin (TX) (Bai and Jiao, 2020; Caspi et al., 2020; Noland, 2020) or by scraping the operators’ openly accessible APIs (e.g., Espinoza et al., 2020; Hawa et al., 2020; McKenzie, 2019). Usual findings include that e-scooters are most frequent near universities, in central business districts and where the bikeways are available (Bai and Jiao, 2020; Caspi et al., 2020; Hawa et al., 2020; Reck et al., 2020; Zuniga-Garcia and Machemehl, 2020), trips are relatively short (i.e. for Louisville, the median distance is 1.3 km, Reck et al., 2020) thus mostly substitute active modes, and precipitation, cold temperatures and wind negatively influence usage (Noland, 2020). There seems to be some uncertainty with regards to usage peaks during the day with some studies finding hints of commuting peaks (Caspi et al., 2020; McKenzie, 2019), while others find single afternoon peaks (Bai and Jiao, 2020; Mathew et al., 2019; Reck et al., 2020). Most studies seem to follow the latter findings and conclude that e-scooters are predominantly used for recreational use instead of commuting, though evidence is slim (McKenzie, 2019; Noland, 2019; Reck et al., 2020).

While most previous studies employ datasets of a single shared micromobility service, only few comparative studies exist (e.g., Campbell et al., 2016; Lazarus et al., 2020; McKenzie, 2019; Younes et al., 2020). Campbell et al. (2016) analysed factors influencing the choice of shared bicycles and shared e-bikes in Beijing employing a stated preference survey. Demand for shared bikes was strongly negatively impacted by trip distance, temperature, precipitation and poor air quality. Demand for shared e-bikes was found to be less sensitive to trip distance, high temperatures and poor air quality, however user socio-demographics had a substantial impact, indicating that only some members of the society were leaning towards this scheme. The authors conclude that while both modes are attractive replacements for other active modes, e-bikes are also an attractive bus replacement while their use for the first/last mile remains to unclear. McKenzie (2019) later compared the spatiotemporal usage patterns of dockless e-scooters with docked bikes in Washington, D.C. Using 3½ months of trip data accessed at a 5-min temporal resolution from the openly accessible API, he found that e-scooter trips exhibit a mid-day peak and a (slight) morning peak and thus are more similar to casual docked bike trips than member trips, which exhibit a clearer commuting pattern with morning and evening peaks. He further analysed trip starts by land use type finding that e-scooter trips mostly originated and terminated in public/recreation areas, whereas bike trips were predominantly home-based commutes. Lazarus et al. (2020) compared docked bike and dockless e-bike usage in San Francisco (CA), using datasets from 02/2018 for one provider each (Ford GoBike and JUMP, respectively). They found that dockless e-bike trips were ~1/3 longer in distance and ~2x longer in duration than docked bike trips. E-Bike trips were further far less sensitive to total elevation gain. Estimating a destination choice model, the authors further found that dockless e-bike trips tended to end in low density areas (suggesting usage for leisure purposes) while docked bike trips tended to end in dense employment areas (suggesting usage for the commute). Finally, Younes et al. (2020) compared the determinants of shared dockless e-scooter and shared docked bike trips (both member and non-member) in Washington, D.C. Using data from the providers' publicly accessible APIs between 12/2018 and 06/2019, they estimate and compared hourly number of trips and hourly median duration of trips. While members of the analysed docked bike scheme showed clear weekday morning and evening commute peaks, casual users of docked bikes and e-scooter users only showed a weekday evening peak. Docked bike trips were ~0.5 km longer than e-scooter trips and weather was less of a disutility for dockless e-scooter users than for docked bike users, which the authors hypothesize to be due to the egress walk often necessary from a docking station. The authors further conducted an initial investigation into the interaction between the two modes by measuring the impact of docked bike trips on dockless e-scooter trips. As expected, the authors found that casual usage had a negative and significant coefficient (implying some possible competition) while membership usage had a positive and significant coefficient (implying some possible complementarity). This analysis, however, is spatially and temporally aggregated and thus it remains uncertain how users decided when facing the choice between two different micromobility providers and modes.

This gap precisely motivates our study. By employing a dataset that comprises trip-level data for multiple shared micromobility providers, we can analyse competition and mode choice between multiple shared micromobility providers at the highest possible spatiotemporal granularity. This has not been studied yet, however becomes an increasingly relevant topic with the steady rise of new providers.

3. Data

3.1. Preparation

We collect our data in Zurich, Switzerland. Zurich is the largest Swiss city with 434K inhabitants (1.5M in the metropolitan area). Zurich is one of Switzerland's economic centres and situated near the Alps. It exhibits elevation differences of up to 480m within the municipal area. Public transport service quality can be considered very high with a stop every 300m in the city by regulation. Thus, it comes as no surprise that the overall modal split of public transport was 41% (walk: 26%, car: 25%, (e-)bike: 8%) in the last Swiss mobility census (2015).

Several micromobility providers operate in Zurich. The most established one is Publibike, which offers docked bikes and e-bikes at ~160 stations. Bond (formerly Smide) offer high quality dockless e-bikes that can travel up to a speed of 45 km/h. Several dockless e-scooter providers have appeared in 2019, among them Lime, Bird, Tier, Voi and Circ.

Our raw dataset consists of scraped vehicle location data from 8 shared micromobility providers[1] in Zurich, Switzerland. Between 8 January and 23 January, we queried each micromobility providers' API every ~60s for all available vehicles, thus collecting over 56M observations. Each observation contains information on a vehicle's location (GPS lon/lat), its type and model, an ID, a timestamp, the provider and, for most providers, the battery level.

Naturally, a vehicle only appears as an observation in our dataset when available to be booked. Conversely, we define a "disappearance" as a trip when, additionally, the following circumstances are given: the time gap has to be at least 2 min long and the (haversine) distance between the origin and the destination has to be at least 200 m (these filters are necessary to prevent GPS inaccuracies falsely being identified as trips). We further filter trips by duration (max 60 min), distance (max 15 km) and speed (max 45 km/h) as faster trips are likely due to GPS inaccuracies and thus non-informative, and longer trips likely to be round trips, thus non-informative as well. As a result, we obtain a total of 48'231 micromobility trips during our 15 days (~3'200 trips per day).

3.2. Validation

We validate the scraped trip data against real booking data which we obtained for 3 of the 8 providers (docked e-bikes, docked bikes, dockless e-bikes) with satisfactory results (see Figure 1). Overall, we correctly identified ~95% of all trips in terms of weekday, time of day and duration. The only bias in our scraped data we were able to detect is fewer short rides for docked e-bikes and bikes (5-12 min) and slightly more longer trips (17+ min), which may be due to "trip chaining" (i.e., if a bike is both returned and rented out again between two queries, the successive rides are identified as one). This hypothesis is confirmed by the observation that the scraped data contains ~5% less trips than the booking data for these two modes.

[1] The 8 shared micromobility providers divide into 5 dockless e-scooter providers, 1 dockless e-bike provider, 1 docked e-bike provider and 1 docked bike provider.

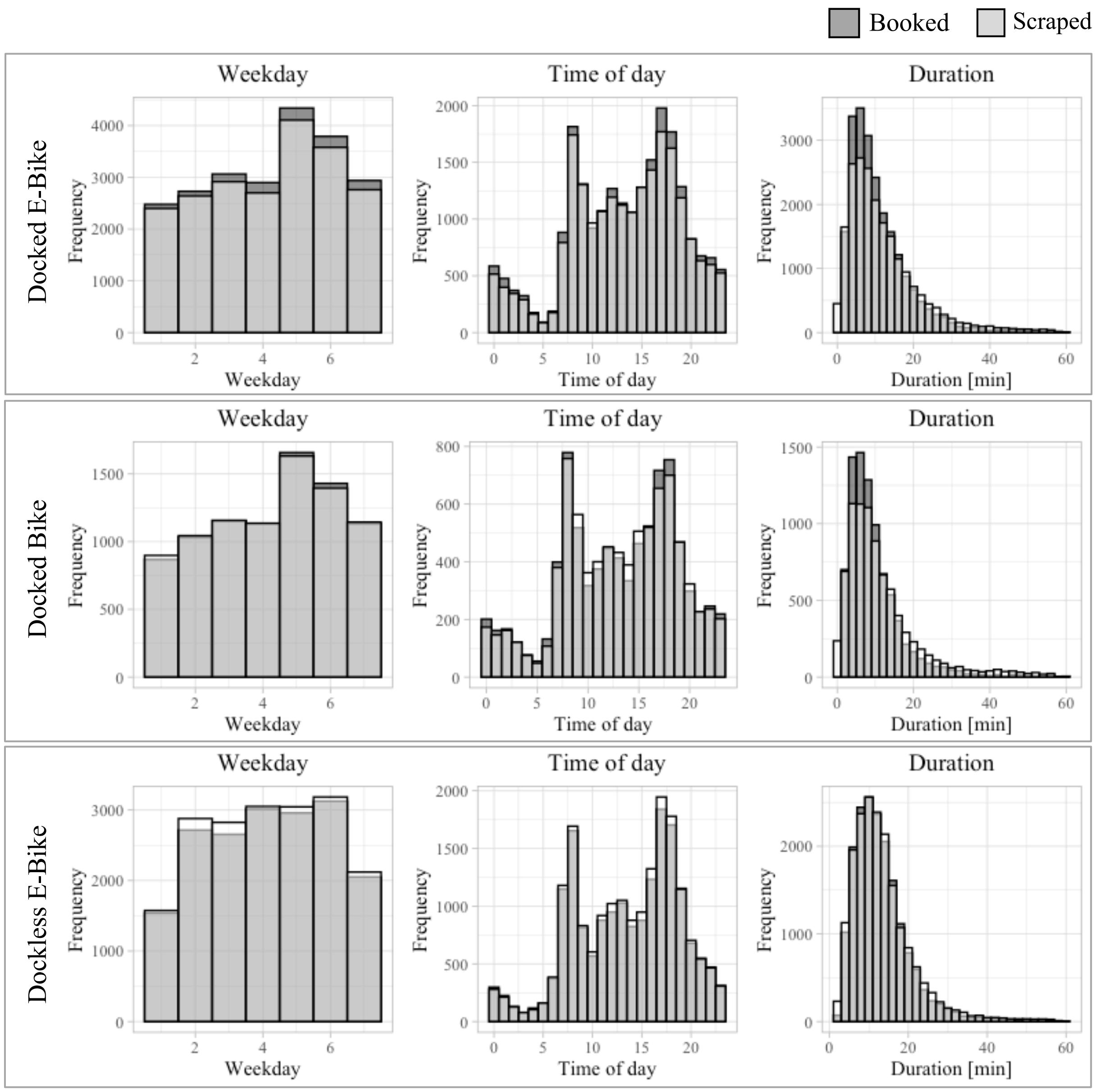

Fig. 1. Validation of scraped trip data vs. real booking data.

3.3. Descriptive analysis

The 48’231 scraped micromobility trips are split between the 8 operators and modes as follows: 17’751 docked e-bike trips, 7’295 docked bike trips, 4’766 dockless e-bike trips and 18’419 dockless e-scooter trips. The dockless e-scooter trips are split into 4 providers: 9’399 provider #1, 8’251 provider #2, 609 provider #3, 160 provider #4. For the subsequent analyses, we exclude dockless e-scooter providers #3 and #4 as they exhibit too few observations.

Figure 2 plots descriptive statistics for all remaining 5 providers (all curves are plotted relative to total number of trips per provider). The plot by time of day shows that shared bikes in general (i.e., dockless e-bike, docked e-bike, docked bike) are used most during the morning and evening peaks. E-scooters on the other hand do not exhibit the morning peak but show a peak at mid-day, in the evening and at night (i.e., between 8 p.m. and 5 a.m.).

The plot by distance shows that e-scooters are mostly used for very short trips (median: 721m) while bikes (median: 1’312m) and e-bikes (median: 1’574m) are used for substantially longer trips. The plot by elevation difference further reveals that docked bikes and e-scooters are mostly used in even terrain (median difference in elevation for bikes: -.46m, sd: 19.7; median difference in elevation for e-scooters: 0.20m, sd:16.7), while e-bikes show a much larger spread in both directions (up-hill and down-hill) (median: -0.16m, sd: 38.8).

The plot by duration is similar to the plot by distance (i.e., shorter durations for e-scooters, longer durations for bikes). The plot by battery level reveals that very few e-scooters and dockless e-bikes show low battery levels (i.e., below 20%) while e-scooters seem to be recharged more often, leading to higher general battery levels and expected “peaks” at 100%. E-Scooter provider #2 exhibits further peaks at 60% and 80%, which we assume to be due to programming of e-scooters’ battery information or charging cycles.

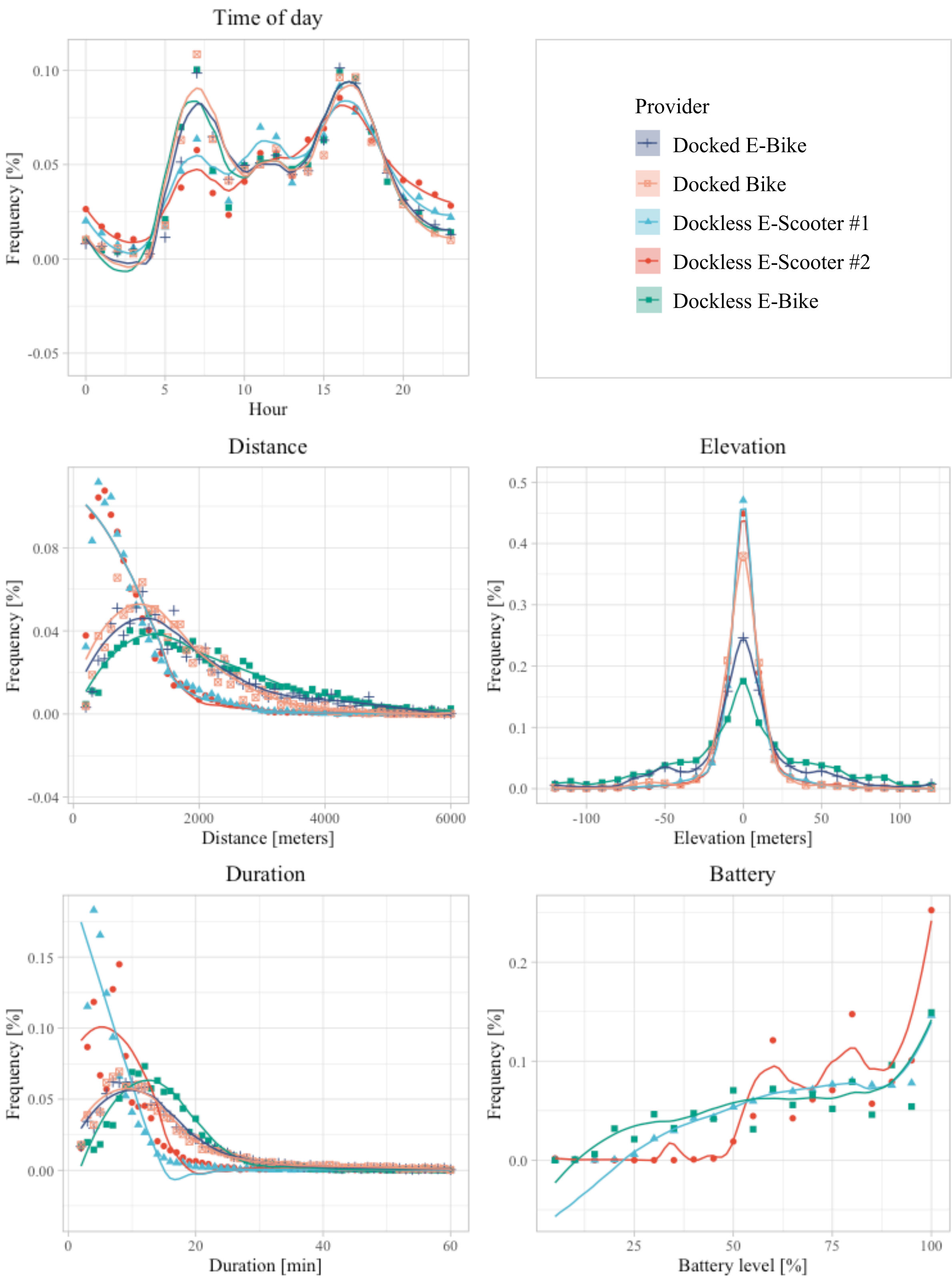

Fig. 2. Exemplary descriptive statistics for shared micromobility providers in Zurich.

4. Methods

We identify "competition situations" as follows. For each trip, we consider the departure location ("origin") and identify all vehicles available within a 5 min walking distance (417 m at 5 km/h walking speed) and within 5 min to departure time. Figure 3 visualizes this approach.

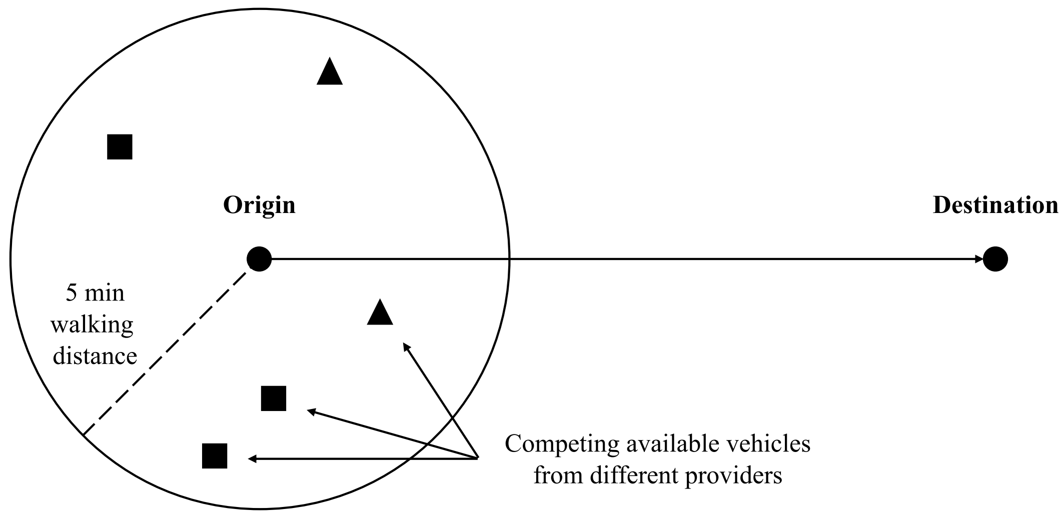

Fig. 3. Identifying competing vehicles.

Using this method, we were able to identify *competing available* providers for 46'436 trips (~97.8%). Each of those trips can thus be interpreted as a choice situation, where one provider was chosen while others were available. Each choice set is composed of a number of available providers and attributes that differentiate each provider, such as the number of available vehicles per provider ("vehicle density") within 5 min walking distance of the origin of the recorded trip, the battery level of the closest vehicle and whether the provider was chosen to conduct the trip, and of attributes that characterize the trip (time of day, elevation difference between origin and destination, distance). Table 1 summarizes all attributes used to define the choice set.

Table 1
Attributes used to define choice sets (excluding time of day).

Attribute	Unit	Provider	Min.	1st Qu.	Med.	Mean	3rd Qu.	Max.
Vehicle density	Count	Dockless E-Scooter #1	0.0	4.0	9.0	13.1	20.0	61.0
		Dockless E-Scooter #2	0.0	4.0	8.0	9.3	13.0	40.0
		Dockless E-Bike	0.0	1.0	2.0	2.9	4.0	21.0
		Docked Bike	0.0	0.0	5.0	13.1	20.0	140.0
		Docked E-Bike	0.0	3.0	9.0	14.7	21.0	111.0
Battery level	%	Dockless E-Scooter #1	0.0	59.0	75.0	73.4	88.0	100.0
		Dockless E-Scooter #2	16.0	52.0	71.0	69.2	89.0	100.0
		Dockless E-Bike	10.0	44.0	67.0	65.1	89.0	100.0
Elevation	Metres		-213.9	-8.2	0.1	0.4	8.6	214.1
Distance	Kilometres		0.2	0.7	1.1	1.4	1.9	9.8

When analysing the resulting competition situations, striking differences in availabilities and choice probability appear (Table 2) which motivate the remainder of this paper. While dockless e-scooter providers are available in 43-44% of all choice situations, they are only chosen in 18-21% of all cases when available (i.e., they are *not* chosen in 79-82% of all cases when available). This rate is even lower for dockless e-bikes, which are only chosen in 11% of all cases when available, while it is substantially higher for docked bikes (27%) and highest for docked e-bikes (47%). What are the causes behind these differences in choice probability?

Table 2
Availabilities and choice probabilities for each provider.

Provider	Available	Chosen	
		Yes	No
Dockless E-Scooter #1	44 %	21 %	79 %
Dockless E-Scooter #2	43 %	18 %	82 %
Dockless E-Bike	34 %	11 %	89 %
Docked Bike	29 %	27 %	73 %
Docked E-Bike	51 %	47 %	53 %

In the following, we analyse the causes behind the different choice probabilities. We begin by exploring bivariate relationships between our choice attributes (cf. Table 1) and the choice probabilities (cf. Table 2) for each provider and mode. Subsequently, we estimate a multinomial logit model (McFadden, 1974) to explore their joint effect on mode choice using the R package "mixl" (Molloy et al., 2019). We specify the utility functions using the attributes presented above and the following abbreviations:

Modes		Attributes	
ES1	Dockless E-Scooter Provider #1	EL	Elevation difference (Destination – Origin)
ES2	Dockless E-Scooter Provider #2	MO	Morning peak (binary)
ES	Dockless E-Scooter Providers (both)	NI	Night (binary)
DLEB	Dockless E-Bike	DE	Vehicle density
DEB	Docked E-Bike	DI	Distance
DBB	Docked Bike	BA	Battery level

Utility functions

$$U_{ES1} = ASC_{ES1} + \beta_{EL_{ES}} * \mathrm{EL} + \beta_{MO_{ES1}} * \mathrm{MO} + \beta_{NI_{ES1}} * \mathrm{NI} + \beta_{DE_{ES1}} * \log(\mathrm{DE_{ES1}}) + \beta_{DI_{ES}} * \mathrm{DI} + \beta_{BA_{ES1}} * \mathrm{BA}$$

$$U_{ES2} = ASC_{ES2} + \beta_{EL_{ES}} * \mathrm{EL} + \beta_{MO_{ES2}} * \mathrm{MO} + \beta_{NI_{ES2}} * \mathrm{NI} + \beta_{DE_{ES2}} * \mathrm{DE_{ES2}} + \beta_{DI_{ES}} * \mathrm{DI} + \beta_{BA_{ES2}} * \log(\mathrm{BA})$$

$$U_{DLEB} = ASC_{DLEB} + \beta_{EL_{DLEB}} * \mathrm{abs(EL)} + \beta_{DE_{DLEB}} * \mathrm{DE_{DLEB}} + \beta_{DI_{DLEB}} * \mathrm{DI} + \beta_{BA_{DLEB}} * \log(\mathrm{BA})$$

$$U_{DEB} = \beta_{EL_{DEB}} * \mathrm{abs(EL)} + \beta_{MO_{DEB}} * \mathrm{MO} + \beta_{NI_{DEB}} * \mathrm{NI} + \beta_{DE_{DEB}} * \log(\mathrm{DE_{DEB}}) + \beta_{DI_{DEB}} * \log(\mathrm{DI})$$

$$U_{DBB} = ASC_{DBB} + \beta_{EL_{DBB}} * \mathrm{EL} + \beta_{MO_{DBB}} * \mathrm{MO} + \beta_{NI_{DBB}} * \mathrm{NI} + \beta_{DE_{DBB}} * \mathrm{DE_{DBB}} + \beta_{DI_{DBB}} * \log(\mathrm{DI})$$

5. Results

5.1. Bivariate relationships

Figure 4 shows plots of bivariate relationships between the choice probability for each provider and mode, and time of day, distance, elevation, vehicle density and battery level. The plot by time of day shows a particularly strong pattern. While docked e-bikes and docked bikes are chosen most during the morning and evening commuting peaks (i.e., between 6 and 9 a.m. and 4 and 7 p.m.), e-scooters show the opposite pattern. They are chosen *least* during these times and most at night (i.e., between 9 p.m. and 5 a.m.). Dockless e-bikes are chosen most during the morning commuting peak while their choice probability remains fairly stable for the rest of the day with a slight dip at night.

The plot by distance shows that as trips get longer, the probability of choosing an e-bike (docked / dockless) sharply rises while simultaneously the probability of choosing an e-scooter drops. Docked bikes show a bell curve with choice probability peaking at ~2’100m and then falling with further distance. The e-scooter and docked e-bike curves cross at a distance of ~650m, which can be interpreted as a competitive advantage of / general preference for docked e-bikes for distances greater than 650m when compared to e-scooters (without considering further factors or interaction effects). Dockless e-bikes and e-scooters cross at a greater distance of ~1’500m.

The plot by elevation shows that the choice probability for e-bikes (docked and dockless) is greater with increasing absolute elevation difference, while the choice probability for docked bikes peaks at the highest possible negative elevation difference (i.e., down-hill) and gradually decreases as elevation rises (up-hill). E-scooters choice probability is highest in flat terrain (i.e., 0 elevation difference).

Vehicle density is measured by number of available vehicles of each provider within 5 min walking distance of observed trip origin. The plot shows an increasing choice probability with increasing vehicle density for all providers as one would expect. Interestingly, however, both the rate (i.e., marginal utility gain) and the intercept differ by mode. Particularly dockless providers (both e-scooters and e-bikes) seem to gain most choice probability from a higher vehicle density. Interestingly, there appears to be a “plateau”, where the maximal choice probability is reached (i.e., where more vehicles on the road do not increase choice probability). For dockless e-scooters, this plateau appears to begin between 15 and 30 e-scooters within 5 min walking distance (i.e., a circle of 417m radius at 5 km/h walking speed). For dockless e-bikes, this plateau seems to begin already at ~10 e-bikes within 5 min walking distance. Docked e-bikes and bikes show higher choice probabilities at lower density levels as well as lower marginal gains from additional vehicles. This could indicate differences in the choice process for docked and dockless micromobility variants. Potential users might decide to take a dockless e-scooter / e-bike only as they see it, while the decision to take a docked bike / e-bike might be decoupled from visual stimuli.

Finally, we explore the impact of the battery level on choice probability. As expected, a higher battery level at departure is related to a higher choice probability. As for vehicle density, there seems to be a plateau at which users are (almost) indifferent to a higher battery charge. For dockless e-bikes, this plateau appears to begin at ~40% battery charge, while for one dockless e-scooter provider it appears to begin at ~50% battery charge. For the other, we observe a stronger, almost linear effect with outliers of much increased choice probability at ~60%, ~80% and 100%. While there is no behavioural explanation for different effects between two e-scooter companies offering the same product, we speculate the effect to be due to rebalancing in high frequency areas after recharging.

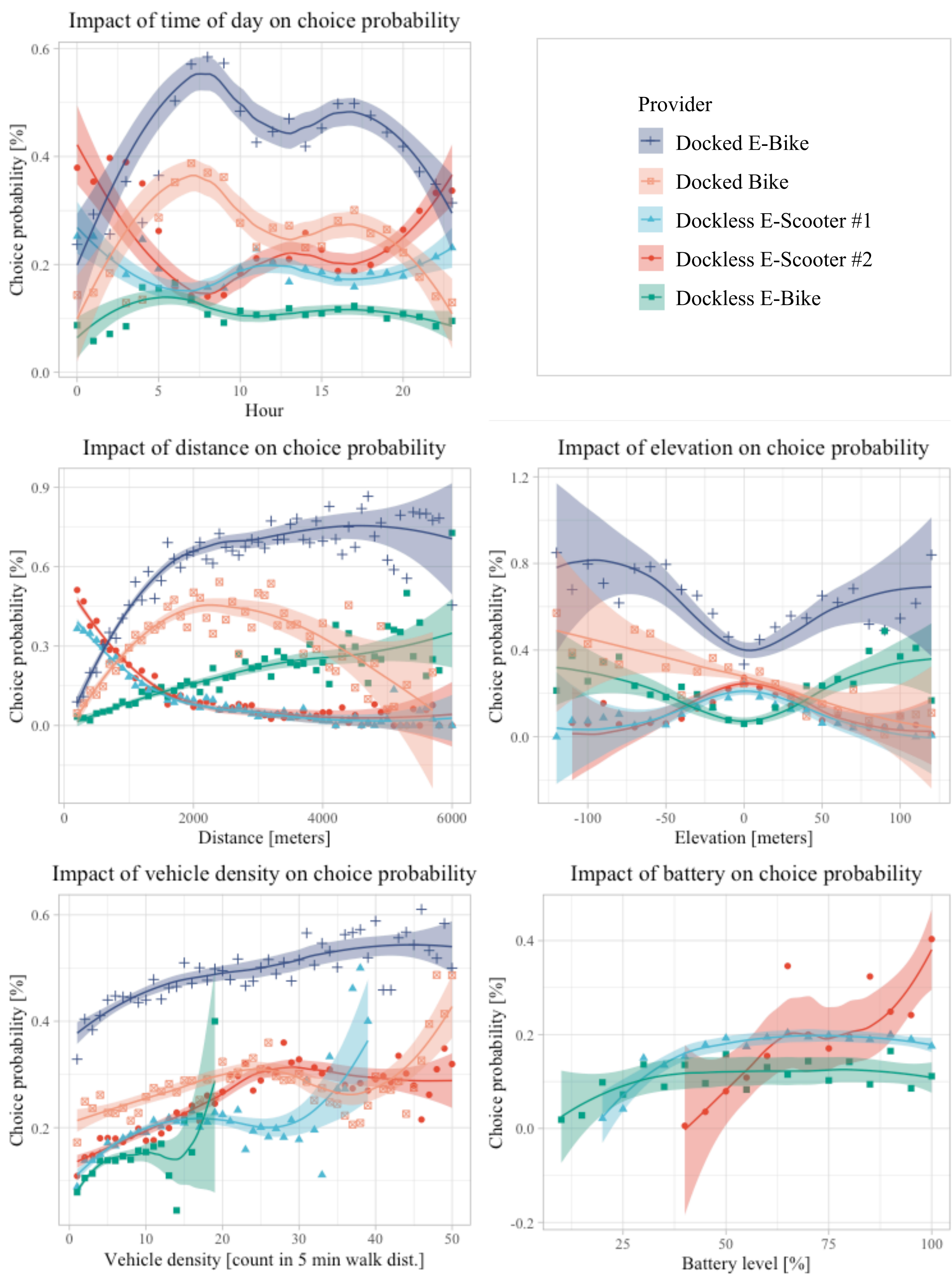

Fig. 4. Bivariate relationships between variables and choice probability.

5.2. Multinomial logit model

We proceed by reporting the results of our mode choice analysis using a multinomial logit model. The overall model has a high McFadden pseudo ρ^2 value of 0.24 using variations of just five trip- and alternative-specific attributes (vehicle density, elevation, time of day, distance and battery level) and no person-specific attributes. We combined the two e-scooter providers where sensible given the bivariate relationships to create the most parsimonious model possible. We further applied transformations where sensible (i.e., where the bivariate plots suggest a logarithmic or absolute-value relationship).

Table 3 displays the results. All coefficients are highly significant and show the expected signs. The Alternative Specific Constants suggest that docked e-bikes have the highest *default* utility (competitive advantage), followed by docked bikes (-0.259), dockless e-scooters (-1.885 and -2.350) and dockless e-bikes (-3.526).

Dockless e-bikes seem to have the highest marginal gain in vehicle density which could be due to the fact that the operator only has few dockless e-bikes deployed (250 for all of Zurich) in comparison to other operators and modes. Docked alternatives gain least from increased vehicle density, which again suggests differences in the decision process (see above).

Both elevation and distance have the strongest and most positive effect for e-bikes. Elevation has a negative effect for docked bikes, which is intuitive as cycling up-hill takes time and energy, and only seems to have a slight effect on e-scooters. Distance, in turn, has a strong and negative influence on e-scooter mode choice.

The morning peak strongly and *positively* influences mode choice for docked micromobility (e-bikes and bikes) and equally strongly but *negatively* for dockless e-scooters. At night, this effect reverses itself (i.e., strong and positive effect on dockless e-scooters and strong and negative effect on docked (e-)bikes. Finally, battery charge positively influences mode choice for all alternatives.

Table 3
Estimation results for the multinomial logit model.

Parameter	Provider	Trans-formation	Coef.	Std.
ASC	Dockless E-Scooter #1		-2.350	***
	Dockless E-Scooter #2		-1.885	***
	Dockless E-Bike		-3.526	***
	Docked Bike		-0.259	***
Vehicle density	Dockless E-Scooter #1	log	0.035	***
	Dockless E-Scooter #2		0.058	***
	Dockless E-Bike		0.167	***
	Docked Bike		0.017	***
	Docked E-Bike	log	0.025	***
Elevation	Dockless E-Scooter		-0.002	**
	Dockless E-Bike	abs	0.026	***
	Docked Bike		-0.010	***
	Docked E-Bike	abs	0.014	***
Morning peak (6 a.m. – 9 a.m.)	Dockless E-Scooter #1		-0.377	***
	Dockless E-Scooter #2		-0.212	***
	Docked Bike		0.170	***
	Docked E-Bike		0.131	***
Night (9 p.m. – 5 a.m.)	Dockless E-Scooter #1		0.829	***
	Dockless E-Scooter #2		0.517	***
	Docked Bike		-0.293	***
	Docked E-Bike		-0.284	***
Distance	Dockless E-Scooter		-0.304	***
	Dockless E-Bike		0.774	***
	Docked Bike	log	1.331	***
	Docked E-Bike	log	1.344	***
Battery level	Dockless E-Scooter #1		0.026	***
	Dockless E-Scooter #2	log	0.309	***
	Dockless E-Bike	log	0.134	***
McFadden pseudo ρ^2			0.24	
AIC			99’552	
n			46’436	

*** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

6. Concluding discussion

As the number of micromobility services continues to grow, an increasing number of users in many cities can choose between several micromobility modes and providers. This raises a number of questions: How does the usage between different modes and providers differ? Which factors influence the choice of a specific mode and provider over others, and how?

Most previous studies have analysed datasets from single providers, thus drawing lessons on the *isolated* usage of each mode. Only few comparative studies between two modes exist and none so-far have analysed competition and mode choice at a high spatiotemporal resolution. To this end, we analysed a large dataset containing trips of 5 different shared micromobility providers and observations for all available vehicles at high spatiotemporal resolution over several weeks, both descriptively and by estimating a mode choice model.

Our results show that users choose docked e-bikes and docked bikes mostly during peak hours while e-scooters peak during off-peak hours. This indicates that docked modes are preferred for commuting, as commuting trips are a major contributor to traffic in peak hours. A primary reason for this tendency may be the fact that for docked services, uncertainty about the spatiotemporal availability of bikes at the trip origin is lower. This may reinforce habit formation with respect to mode choice for the commute.

The choice probability for e-bikes (docked and dockless) tends to increase with distance, while the probability of choosing an e-scooter decreases. This can be readily explained by the advantage of e-bikes in terms of comfort and lower physical exertion for longer trips. Bicycles generally tend to be more comfortable for longer trips than e-scooters, but e-bikes keep this advantage also for very long trips, as aerobic endurance is less important due to the electric motorization. Elevation patterns support this explanation: e-bikes tend to be preferred for uphill trips.

The bivariate relationships show a pronounced effect of vehicle density on the choice of dockless e-bikes and e-scooters. This is an indication that availability tends to be a limiting factor for these modes. Interestingly, there appears to be a “plateau”, where the maximal choice probability is reached (i.e., where more vehicles on the road do not increase choice probability, or the “marginal utility gain” is close to 0). For dockless e-scooters, this plateau appears to begin between 15 and 30 e-scooters within 5 min walking distance, while for dockless e-bikes, this plateau seems to begin already at ~10 e-bikes. Docked e-bikes and bikes show higher choice probabilities at lower density levels as well as lower marginal gains from additional vehicles. These findings could indicate differences in the choice process for docked and dockless micromobility variants. Potential users might decide to take a dockless e-scooter / e-bike only as they see it, while the decision to take a docked bike / e-bike might be decoupled from visual stimuli.

The battery level has a strong effect on the choice of e-scooters, while it does not seem to strongly affect the choice of e-bikes. A potential explanation may be that a low battery level of e-scooters has a more immediate effect on the potential range and speed, and that batteries of e-bikes used in Zurich’s high-end e-bikes have a much higher maximum charge than batteries of e-scooters. As for vehicle density, there seems to be a plateau at which users are (almost) indifferent to a higher battery charge. For dockless e-bikes, this plateau appears to begin at ~40% battery charge, while for one dockless e-scooter provider it appears to begin at ~50% battery charge.

We plan several next steps to expand this research. First, we plan to include other factors such as price, weather and interaction effects between our current factors (e.g., elevation and distance). Second, we plan to explore different functional forms for our variables and estimated a nested logit model to test different, multi-level structures of potential decision-making processes (e.g., docked vs dockless choice before mode and provider choice; mode choice before provider choice). Third, we plan to expand the scope of our analysis temporally by including several more weeks of Zurich data, and geographically, by adding Basel as a second Swiss city to contextualize results.

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