Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland
Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland

Daniel J. Reck¹*, Sergio Guidon¹b, He Haitao², Kay W. Axhausen¹

¹ Institute for Transport Planning and Systems, ETH Zürich, CH.
² Institute of Science, Technology and Policy, ETH Zürich, CH.
³ School of Architecture, Building and Civil Engineering, Loughborough University, UK.
* Corresponding author (reckd@ethz.ch).

Abstract

Shared micromobility services (e-scooters, bikes, e-bikes) have rapidly gained popularity in the past few years, yet little is known about their usage. While most previous studies have analysed datasets from single providers, only few comparative studies of two modes exist and none so far have analysed competition or mode choice at a high spatiotemporal resolution for more than two modes. To this end, we develop a generally applicable methodology to model and analyse shared micromobility competition and mode choice using widely accessible vehicle location data. We apply this methodology to estimate the first comprehensive mode choice models between four different micromobility modes using the largest and densest empirical shared micromobility dataset to-date (~169M vehicle locations collected in Zurich over two months). Our results suggest that mode choice is nested and dominated by distance and time of day. Docked modes are preferred for commuting. Hence, docking infrastructure for currently dockless modes could be vital for bolstering micromobility as an attractive alternative to private cars to tackle urban congestion during rush hours. Furthermore, our results reveal a fundamental relationship between fleet density and usage. A "plateau effect" is observed with decreasing marginal utility gains for increasing fleet densities. City authorities and service providers can leverage this quantitative relationship to develop evidence-based micromobility regulation and optimise their fleet deployment, respectively.

Keywords: micromobility, e-scooter, e-bike, bikesharing, competition, mode choice

Preprint, paper submitted to Transportation Research Part C: Emerging Technologies
1. Introduction

Recent technological development has accelerated the emergence of shared micromobility services including dockless e-scooters, dockless and docked bikes and e-bikes. The variety and availability of such services in major cities worldwide have grown rapidly, allowing an increasing number of users to choose between several modes and providers. Meanwhile, policymakers are often struggling to develop pertinent regulation as the usage of shared micromobility is not yet well understood. Fundamental questions that need to be answered are how travellers adopt and use each mode, how usage varies between different modes, and how they impact urban mobility and its sustainability overall.

The scope of the existing body of knowledge on shared micromobility from empirical research varies by mode. While shared docked bikes are relatively well understood (e.g., Bachand-Marleau et al., 2012; DeMaio, 2009; Fishman et al., 2013; Shaheen et al., 2010), the literature on dockless (e-)bikes is evolving and still limited in scope (e.g., Campbell et al., 2016; Du et al., 2019; Guidon et al., 2019; He et al., 2019; Shen et al., 2018). Dockless e-scooters are the latest addition to the micromobility mix and have only recently been looked into (e.g., Bai and Jiao, 2020; Eccarius and Lu, 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 a few comparative studies of two modes exist (e.g., Campbell et al., 2016; Lazarus et al., 2020; McKenzie, 2019; Younes et al., 2020; Zhu et al., 2020). To the authors' best knowledge, there is not yet any literature on the usage, competition, and mode choice for more than two shared micromobility modes at a high spatiotemporal resolution.

It is critical to fill this knowledge gap both for the scientific community and for the practical realm. First, understanding mode choice (and underlying user preferences) is the quintessential first step towards including micromobility modes in transport network simulations to analyse (and predict) their impact at the system level (where micromobility at scale has not been introduced yet). Second, it clarifies their potential to substitute car trips, alleviate roads during the commute and reduce the footprint of urban transport and thus enables evidence-based policymaking (e.g., vehicle licensing, parking space allocation). Third, it provides insights into trade-offs and marginal effects, enabling existing providers to further optimize their operations (e.g., vehicle repositioning and charging by time of day) and prospective providers to evaluate their competitive positions.

To this end, this paper estimates the first mode choice models between four different shared micromobility modes (dockless e-scooters, dockless e-bikes, docked e-bikes and docked bikes) at a high spatiotemporal resolution. We develop an innovative methodology to model and analyse shared micromobility competition and mode choice using only vehicle location data. Such data is widely accessible through a variety of data collection methods such as scraping openly accessible provider APIs. Therefore, our proposed methodology is generally applicable to analyse these issues regardless of the location. To illustrate the methodology, we estimate the first comprehensive mode choice models between four different micromobility modes in Zurich using the largest and densest empirical shared micromobility dataset to-date.

The remainder of this article is organised as follows. In Section 2, we review the literature on shared micromobility with a particular focus on usage and mode choice. In Section 3, we introduce our dataset both conceptually and descriptively. In Section 4, we develop our methodology used to analyse bivariate relationships and estimate the mode choice models. We present our results in Section 5, discuss their implications for research, policy and practice in Section 6, and close with a summary and possible extensions of our work in Section 7.
2. Literature review

The number and variety of shared micromobility services have rapidly 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 categorised mainly into supply- and demand-side topics, of which the latter is more relevant to this paper. Demand-side research on shared micromobility tends to focus on questions such as how and why specific services are used. Demand-side research can be further categorised 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). The latter two are most relevant to the topic of this paper and thus the 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 that 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, the same effect is found to be negative during weekends. In conjunction with often observed morning and evening demand peaks, this suggests that an important driver of demand is the commute (e.g., Bordagaray et al., 2016; Lathia et al., 2012; McKenzie, 2019; Zhao et al., 2015). Adverse weather (precipitation, wind) usually has a negative influence on use, while agreeable weather conditions are associated with higher levels of usage. Finally, docked bikes have been found to primarily substitute walking and public transport trips instead of private cars (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, e-bike-sharing systems have gained substantial scholarly attention. While external factors have generally been found to be similar to docked bikesharing, trips with shared e-bikes tend to be longer (i.e., between 2 and 3 km), and elevation does not appear to influence the use of e-bikes (Campbell et al., 2016; Du et al., 2019; 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. Only few peer-reviewed academic studies examine external factors influencing user demand. Most studies have been conducted using the publicly available booking datasets from Louisville (KY) and Austin (TX) (Bai and Jiao, 2020; Caspi et al., 2020; Noland, 2019; Noland, 2020; Reck et al., 2020a) or by scraping the operators' openly accessible APIs (e.g., Espinoza et al., 2020; Hawa et al., 2020; McKenzie, 2019). Results from the above research show that e-scooters are most used 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). Also, trips are relatively short. For example, the median distance for Louisville, is 1.3 km (Reck et al., 2020a). Precipitation, low temperatures and wind negatively influence their usage (Noland, 2020). There is some uncertainty with regards to usage peaks during the day. Some studies find 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., 2020a). Most studies follow the latter findings and conclude that e-scooters are predominantly used for recreational use instead of commuting, though available evidence is slim (McKenzie, 2019; Noland, 2019; Reck et al., 2020a).
While most previous studies employ datasets of a single shared micromobility service, only few comparative studies exist (i.e., Campbell et al., 2016; Lazarus et al., 2020; McKenzie, 2019; Younes et al., 2020; Zhu et al., 2020). Campbell et al. (2016) analysed factors influencing the choice between shared bicycles and shared e-bikes in Beijing by employing a stated preference survey. Demand for shared bikes was strongly negatively impacted by trip distance, high 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. User socio-demographics had a substantial impact, indicating that only some parts of the society had a preference for shared e-bikes. 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 unclear. McKenzie (2019) later compared the spatiotemporal usage patterns of dockless e-scooters (Lime) with docked bikes (Capital Bikeshare) in Washington, D.C. Using 3½ months of trip data accessed at a 5-min temporal resolution from the openly accessible APIs, the author found that e-scooter trips exhibit a mid-day peak and a (slight) morning peak and were thus similar to docked bike trips conducted by casual users. Docked bike trips conducted by frequent users, on the other hand, exhibited a clearer commuting pattern with morning and evening peaks. The study further analysed trip starts by land-use type finding that e-scooter trips mostly originated and terminated in public/recreation areas. In contrast, bike trips were predominantly identified as home-based commutes. Zhu et al. (2020) compared fleets and usage patterns of docked bike-sharing and dockless e-scooter sharing in Singapore. Using data from the operators’ publicly accessible APIs for one month each (bike-sharing: 08/2017, e-scooters: 02/2019), they found that shared e-scooters form a spatially more compact and denser vehicle network than shared bikes. High demand was associated with tourist attractions, metro stations and residential areas. Rainfall and high temperatures suppressed demand for both modes. Lazarus et al. (2020) compared docked bike (Ford GoBike) and dockless e-bike (JUMP) usage in San Francisco (CA), using datasets from 02/2018 for one provider each. 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 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). In contrast, 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 (six providers) and shared docked bike trips (Capital Bikeshare) in Washington, D.C. Using data from the providers' publicly accessible APIs between 12/2018 and 06/2019, they estimated and compared the hourly number of trips and the 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. The authors explain these results with the egress walk often necessary from a docking station. They 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 using a negative binomial regression model. As expected, the authors found that casual usage had a small negative and significant coefficient. This implies potential competition. In contrast, regular usage had a small positive and significant coefficient. This implies potential complementarity.

We identify two gaps in the reviewed literature. First, Younes et al. (2020) are the first and only authors to our knowledge to analyse possible competition between different micromobility modes, however their analysis is temporally and spatially aggregated (i.e., the dependent variable is hourly number of trips in Washington, D.C.) and they only analyse the effect of docked bikesharing trips on e-scooter trips. A natural extension of their work is to analyse the effect of several different micromobility modes (e.g., docked bikes, docked e-bikes, dockless e-bikes, dockless e-scooters) on each other by estimating
a mode choice model at a high spatiotemporal resolution (i.e., by identifying actual choice situations where several different modes are available to the user at a specific time and place). While previous studies could only reveal shares of observed trips, a mode choice model could reveal the underlying preferences. Second, all previous comparative studies using trip data have been conducted between two micromobility modes only (and indeed only in two variations, i.e., dockless e-scooters and docked bikes in McKenzie, 2019, Younes et al., 2020 and Zhu et al., 2020; docked bikes and dockless e-bikes in Lazarus et al., 2020) with varying temporal resolution (i.e., 1-5 min scraping intervals). We thus don't know how the usage compares between more than two modes and in combinations that have not been explored yet (e.g., dockless e-scooters and dockless e-bikes, docked e-bikes and dockless e-bikes). Cross-inference from one place to another (even within the US) is difficult as city structures and travel flows vary substantially (evidence of usage peaks for dockless e-scooters in some cities but not in others supports this statement, see above). We also don't know how micromobility services are used anywhere outside of the US as rigorous peer-reviewed studies have not appeared yet. Thus, a comprehensive comparison of many different micromobility modes (e.g., docked bikes, docked e-bikes, dockless e-bikes, dockless e-scooters) at high spatiotemporal resolution could improve our current (limited) understanding of the similarities and differences in usage.

This research aims to fill these gaps by developing a generally applicable methodology to model and analyse shared micromobility usage, competition and mode choice at a high spatiotemporal resolution using widely accessible vehicle location data. We estimate the first comprehensive mode choice models between 4 different shared micromobility modes leveraging the largest and densest empirical shared micromobility dataset to-date.

3. Data

3.1. Collection

We collect data in Zurich, Switzerland. Zurich is the largest Swiss city with 434K inhabitants (1.5M in the metropolitan area). It is one of Switzerland's economic centres and has high-quality public transport with a stop within 300m of each resident in the city. The overall modal split of public transport was 41% walk: 26%, car: 25%, (e-)bike: 8% in the latest Swiss mobility census (2015). Several micromobility providers operate in Zurich. The most established is Publibike, which offers docked bikes and e-bikes at ~160 stations. Bond (formerly Smide) offers dockless e-bikes that can travel up to a speed of 45 km/h. Multiple dockless e-scooter providers started operating since 2019, among them Lime, Bird, Tier, Voi and Circ.

Our raw dataset consists of vehicle location data from 5 shared micromobility providers in Zurich, Switzerland. Between 1 January and 29 February 2020, we queried each micromobility providers' API every ~60s for all available vehicles, thus collecting over 169M 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 dockless providers, the battery charge. Each vehicle appears as a sequence of observations over time in our dataset only when it is available to be booked. Conversely, we define a disappearance of a previously observed vehicle as a trip. It is, however, necessary to remove falsely identified trips due to GPS inaccuracies. Thus, the following conditions have to be satisfied for a disappearance to be considered a trip: (1) the time gap is at least 2 minutes and at most 1 hour, (2) the great-circle distance between the origin and the destination is at least 200 meters and at most 15 kilometres, and (3) the average speed is at most 45 km/h. Overall, we obtain 168'895 micromobility trips during the two months of analysis (~2'800 trips per day).
3.2. Validation

We validate the calculated trips against actual trips (from booking data) which we obtained for 3 of the 5 providers (docked e-bikes, docked bikes, dockless e-bikes) with satisfactory results. Overall, we correctly identified ~95% of all trips in terms of origin/destination, weekday, time of day and duration. The only bias that we detected 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 there are ~5% fewer calculated trips than actual trips for these two modes.

3.3. Descriptive analysis

We separate the 168'895 micromobility trips into the 5 corresponding providers and modes: 67'114 docked e-bike trips, 25'167 docked bike trips, 14'684 dockless e-bike trips, 31'920 dockless e-scooter trips (provider #1) and 30'010 dockless e-scooter trips (provider #2).

| Docked E-Bike | Docked Bike | Dockless E-Scooter #1 | Dockless E-Scooter #2 | Dockless E-Bike |
|----------------|-------------|-----------------------|-----------------------|-----------------|

**Fig. 1.** Descriptive statistics for trips conducted with 5 shared micromobility providers in Zurich (smoothed lines).
Figure 1 shows descriptive plots for the calculated trips by provider. Note that all curves are plotted relative to the 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. In contrast, e-scooters exhibit a much smaller morning peak, a pronounced evening peak and much higher usage frequencies at night than shared bikes (i.e., between 8 p.m. and 4 a.m.).

The plot by trip distance shows that e-scooters from both providers are mostly used for very short trips (median: 730m) while bikes (median: 1'292m) and e-bikes (median: 1'595m) 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 (bikes: 25%-quantile: -7.51m, median: -.45m, 75%-quantile: 6.12m; e-scooters: 25%-quantile: -5.43, median: 0.15m, 75%-quantile: 5.95), while e-bikes show a larger spread in both directions (up-hill and down-hill) (25%-quantile: -14.26, median: 0.00m, 75%-quantile: 13.90m).

The plot by battery charge reveals that very few e-scooters and dockless e-bikes show low battery charges (i.e., below 20%) at trip start. This indicates that battery charge might be a relevant criterion for mode choice. 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.

4. Methodology

We identify choice sets from vehicle location data and vehicle trip data as follows. For each trip, we identify all vehicles available within a 2 min walking distance (167 m at 5 km/h walking speed) from the departure location and within 2 min to departure time (Figure 2). Note that micromobility trips are generally short, especially those made with e-scooters. It is therefore unlikely that users are willing to walk a substantially longer distance to access a vehicle.

Using this method, we were able to identify competing available providers for 139'559 trips (~82.6%). For each of those trips, we can thus define a choice situation, where one provider was chosen while others were available. Each choice set is composed of a number (1 to 5) of available providers and attributes that vary by provider. This includes the number of available vehicles per provider ("vehicle density") within 2 min walking distance from the departure location, the battery charge (only available for three providers), prices and whether the provider was chosen to conduct the trip. Additionally,
attributes that vary by trip include time of day, elevation difference between origin and destination, distance). Table 1 summarises the 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  | 0.0     | 1.0  | 2.2  | 3.0     | 37.0 |
|              |      | Dockless E-Scooter #2    | 0.0  | 1.0     | 2.0  | 2.6  | 4.0     | 26.0 |
|              |      | Dockless E-Bike          | 0.0  | 0.0     | 0.0  | 0.7  | 1.0     | 11.0 |
|              |      | Docked Bike              | 0.0  | 0.0     | 0.0  | 3.2  | 4.0     | 66.0 |
|              |      | Docked E-Bike            | 0.0  | 0.0     | 2.0  | 5.6  | 7.0     | 120.0|
| Battery charge | %    | Dockless E-Scooter #1    | 0.0  | 57.0    | 74.0 | 72.0 | 89.0    | 100.0|
|              |      | Dockless E-Scooter #2    | 0.0  | 52.0    | 71.0 | 69.0 | 88.0    | 100.0|
|              |      | Dockless E-Bike          | 10.0 | 47.0    | 71.0 | 68.0 | 91.0    | 100.0|
| Price       | CHF  | Dockless E-Scooter #1    | 1.7  | 3.1     | 4.2  | 5.1  | 6.2     | 21.6 |
|              |      | Dockless E-Scooter #2    | 1.8  | 3.4     | 4.6  | 5.7  | 7.0     | 24.6 |
|              |      | Dockless E-Bike          | 0.5  | 1.5     | 2.2  | 2.9  | 3.8     | 14.8 |
| Elevation   | Metres | -203.0     | -7.3 | 0.5     | 1.8  | 9.1  | 235.4   |
| Distance    | Kilometres | 0.2      | 0.7  | 1.2    | 1.5  | 1.9  | 10.1   |

Note that the price was only calculated for dockless providers as they have simple pricing mechanisms. There is an unlocking cost of 1 CHF for both dockless e-scooter providers and a per-minute cost for all three providers (0.25 CHF for dockless e-bikes, 0.35 CHF for dockless e-scooter provider #1 and 0.40 CHF for dockless e-scooter provider #1). Price structures for docked modes are more complex as several different membership schemes granting discounts of up to 100% for rides up to 30 min are available and commonly used. As we do not have access to user-specific information, especially regarding the membership schemes, price variables for these two modes are not included.

### Table 2
Number of vehicles, availabilities and choice probabilities for each provider.

| Provider          | Number of vehicles | Availability in choice situations | Chosen (when available) |
|-------------------|--------------------|-----------------------------------|-------------------------|
|                   |                    | Yes     | No     | Yes     | No     |
| Dockless E-Scooter #1 | 693               | 62 %    | 29 %   | 29 %    | 71 %   |
| Dockless E-Scooter #2 | 766               | 85 %    | 20 %   | 20 %    | 80 %   |
| Dockless E-Bike   | 241                | 44 %    | 19 %   | 19 %    | 81 %   |
| Docked Bike       | 762                | 39 %    | 40 %   | 40 %    | 60 %   |
| Docked E-Bike     | 841                | 63 %    | 64 %   | 64 %    | 36 %   |

1 CHF = 1.03 USD at the time of writing (25 May 2020).  
2 In personal communication, the docked (e-)bike providers stated that ~90% of all trips were conducted by members that have subscribed to discount schemes allowing unlimited free rides up to a duration of 30 min.
When analysing the resulting competition, striking differences in availabilities and choice probabilities appear (Table 2) which motivate the remainder of this paper. While dockless e-scooter providers are available in 62-85% of all choice situations, they are only chosen in 20-29% of all cases when available (i.e., they are not chosen in 71-80% of all cases when available). This rate is even lower for dockless e-bikes, which are only chosen in 19% of all cases, while it is substantially higher for docked bikes (40%) and highest for docked e-bikes (64%).

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 (MNL) (McFadden, 1974) to explore their joint effect on mode choice. Choice behaviour could also be nested as some users might only be member of certain types of shared micromobility schemes (i.e., docked bikes or shared e-scooters). We therefore also estimate a model with nested error terms (normal error component logit-mixture model, NECLM) (Walker et al., 2007). We estimate both models iteratively (i.e., dropping insignificant and insubstantial variables and combining variables for similar modes where sensible to obtain a parsimonious model that simultaneously allows for cross-modal comparisons) using maximum likelihood estimation and the R package "mixl" (Molloy et al., 2019). We specify the utility functions using the attributes presented above and the following abbreviations. \( \sigma \) denotes the nested error component, which is only applied in the NECLM model.

| Modes                  | Attributes                  | Utility functions                                      |
|------------------------|-----------------------------|-------------------------------------------------------|
| ES1 Dockless E-Scooter Provider #1 | EL Total elevation gain    | \( U_{ES1} = ASC_{ES1} + \beta_{MO_{ES1}} \cdot MO + \beta_{NI_{ES1}} \cdot NI + \beta_{DE_{ES1}} \cdot DE_{ES1} + \beta_{DI_{ES1}} \cdot DI + \beta_{BA_{ES1}} \cdot BA_{ES1} + \beta_{PR_{ES1}} \cdot PR_{ES1} \) |
| ES2 Dockless E-Scooter Provider #2 | MO Morning peak (binary)   | \( U_{ES2} = ASC_{ES2} + \beta_{MO_{ES2}} \cdot MO + \beta_{NI_{ES2}} \cdot NI + \beta_{DE_{ES2}} \cdot DE_{ES2} + \beta_{DI_{ES2}} \cdot DI + \beta_{BA_{ES2}} \cdot BA_{ES2} + \beta_{PR_{ES2}} \cdot PR_{ES2} \) |
| ES Dockless E-Scooter Providers (both) | NI Night (binary)         | \( U_{DLEB} = ASC_{DLEB} + \beta_{EL_{DLEB}} \cdot EL + \beta_{DE_{DLEB}} \cdot DE_{DLEB} + \beta_{DI_{DLEB}} \cdot DI + \beta_{BA_{DLEB}} \cdot BA_{DLEB} + \beta_{PR_{DLEB}} \cdot PR_{DLEB} \) |
| DLEB Dockless E-Bike     | DE Vehicle density         | \( U_{DBB} = ASC_{DBB} + \beta_{EL_{DBB}} \cdot EL + \beta_{MO_{DBB}} \cdot MO + \beta_{NI_{DBB}} \cdot NI + \beta_{DE_{DBB}} \cdot DE_{DBB} + \beta_{DI_{DBB}} \cdot DI + \beta_{BA_{DBB}} \cdot BA_{DBB} + \beta_{PR_{DBB}} \cdot PR_{DBB} \) |
| DEB Docked E-Bike       | DI Distance                | \( U_{DEB} = ASC_{DEB} + \beta_{EL_{DEB}} \cdot EL + \beta_{MO_{DEB}} \cdot MO + \beta_{NI_{DEB}} \cdot NI + \beta_{DE_{DEB}} \cdot DE_{DEB} + \beta_{DI_{DEB}} \cdot DI + \beta_{BA_{DEB}} \cdot BA_{DEB} + \beta_{PR_{DEB}} \cdot PR_{DEB} \) |
| DBB Docked Bike         | BA Battery charge          | \( U_{DEB} = ASC_{DEB} + \beta_{EL_{DEB}} \cdot EL + \beta_{MO_{DEB}} \cdot MO + \beta_{NI_{DEB}} \cdot NI + \beta_{DE_{DEB}} \cdot DE_{DEB} + \beta_{DI_{DEB}} \cdot DI + \beta_{BA_{DEB}} \cdot BA_{DEB} + \beta_{PR_{DEB}} \cdot PR_{DEB} \) |
|                       | PR Price                   | \( U_{DEB} = ASC_{DEB} + \beta_{EL_{DEB}} \cdot EL + \beta_{MO_{DEB}} \cdot MO + \beta_{NI_{DEB}} \cdot NI + \beta_{DE_{DEB}} \cdot DE_{DEB} + \beta_{DI_{DEB}} \cdot DI + \beta_{BA_{DEB}} \cdot BA_{DEB} + \beta_{PR_{DEB}} \cdot PR_{DEB} \) |

**5. Results**

**5.1. Bivariate relationships**

Figure 3 shows plots of bivariate relationships between the choice probability (i.e., the average likelihood of choosing a particular mode over others) for each provider and mode, and time of day, distance, elevation, battery charge, vehicle density and price. 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 early morning (i.e., between 4 and 7 a.m.) while their choice probability remains fairly stable for the rest of the day with a slight dip at night.

Fig. 3. Bivariate relationships between variables and choice probability (smoothed lines).
Note the interesting difference between these plots and the descriptive plots (Figure 1) where e-scooters show a slight morning peak and a pronounced evening peak. The difference in plots stems from the difference in methods. Previously (Figure 1), we calculated the share of e-scooter trips observed during a particular time bin relative to the total number of e-scooter trips over all time bins. Here (Figure 3), we calculate the choice probability, i.e. the number of times an e-scooter was chosen over another available mode during a particular time bin relative to the total number of times an e-scooter was available during a particular time bin. While the descriptive plots (Figure 1) thus only reveal shares of observed trips, the bivariate plots (Figure 3) reveal preferences in choice situations.

The plot by distance shows that as trips get longer, the probability of choosing an e-bike (docked / dockless) sharply increases 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. In contrast, 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-scooter choice probability is highest in flat terrain (i.e., 0 elevation difference).

Next, we explore the impact of the battery charge on choice probability. As expected, a higher battery charge at departure is related to a higher choice probability. Interestingly, there is a plateau for two providers (dockless e-scooter provider #2 and dockless e-bike provider) at which users are (almost) indifferent to a higher battery charge. From a consumer perspective, this represents decreasing marginal utility gains from increasing battery charge. For dockless e-bikes, this plateau (or "saturation point") appears to begin at ~30% battery charge, while for dockless e-scooter provider #2 it appears to begin at ~50% battery charge. The difference can be explained with stronger batteries and propulsion of e-bikes vs e-scooters, yielding a higher resistance to choose a low-charged e-scooter that might run out of power during the journey. The variation in battery charges is much higher for dockless e-scooter provider #1 with several outliers. While there is no behavioural explanation for different effects between two dockless e-scooter providers offering the same product, we speculate the effect to be due to rebalancing in high-frequency areas after recharging or different recharging practices.

Vehicle density is measured as the number of available vehicles of each provider within 2 min walking distance of the trip departure location. The plot shows an increasing choice probability with increasing vehicle density for all providers as one would expect. Both the rate (i.e., marginal utility gain) and the intercept differ by mode, however. Dockless providers in particular (both e-scooters and e-bikes) gain from a higher vehicle density (steepest slope), while the gain is much less pronounced for docked e-bikes and almost non-existent for docked bikes. Inversely, the choice probability at low vehicle density is much higher for docked e-bikes and bikes than for dockless modes. This indicates 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 (visually or in their app). In contrast, the decision to take a docked bike / e-bike might be decoupled from visual stimuli as usage is more habitual due to knowledge about the locations of the docking stations. It could also be evidence that user groups of
Docked and dockless modes are distinct and that users typically only register with one type of shared micromobility mode.

We observe a plateau-effect for dockless e-scooters in vehicle density. As vehicle densities of dockless modes are generally much lower than those of docked modes, we plot vehicle density again (Figure 4) with a focus on lower numbers (0-30) to better illustrate this effect. Here, we can observe lower marginal utility gains for docked modes than for dockless modes, and decreasing marginal utility gains for e-scooters. The plateau can be interpreted as a saturation point, where higher density does not increase choice probability. For dockless e-scooters, this plateau appears to begin between 10 to 15 e-scooters within 2 min walking distance (i.e., a circle of 167 m radius at 5 km/h walking speed). The difference between the two dockless e-scooter providers could stem from different repositioning practices, for example, how many vehicles are placed and how closely they are placed to each other after recharging.

Fig. 4. Evidence of decreasing marginal utility gains ("plateau effect") for battery charge and vehicle density (smoothed lines).

5.2. Mode choice model estimation

This section reports the estimation results of the mode choice models, which complement the bivariate plots as they reveal the joint effects of all attributes and competition effects between the different modes. The basic MNL model already has an excellent fit\(^3\) with a McFadden pseudo R2 (McFadden, 1974) of 0.31 using variations of just six trip- and alternative-specific attributes (vehicle density, elevation, price, time of day, distance and battery charge) and no person-specific attributes. The normal error component logit-mixture model (NECLM) with two nests (docked / dockless) further improves the fit to a McFadden pseudo R2 of 0.35 (the nested error component \(\sigma\) is highly significant) indicating that indeed there appears to be the expected hierarchy in the decision-making process.

---

\(^3\) McFadden (1979, p. 306) notes "Those unfamiliar with the \(\rho^2\) should be forewarned that its values tend to be considerably lower than those of the R\(^2\) index and should not be judged by the standards for a "good fit" in ordinary regression analysis. For example, values of .2 to .4 for \(\rho^2\) represent and excellent fit."
### Table 3
Estimation results.

| Provider       | Parameter                  | MNL       | NECLM      |
|----------------|----------------------------|-----------|------------|
|                |                            | EST      | SE         | EST      | SE         |
| Dockless       | ASC                        | -1.94*** | 0.05       | -5.01*** | 0.16       |
| E-Scooter      | Distance<sup>1</sup>       | -0.10*** | 0.03       | 1.77***  | 0.11       |
| Provider #1    | Price                      | -0.10*** | 0.00       | -0.46*** | 0.02       |
|                | Vehicle density            | 0.14***  | 0.00       | 0.21***  | 0.00       |
|                | Morning (6 a.m. - 9 a.m.)  | -0.25*** | 0.04       | -0.35*** | 0.05       |
|                | Night (9 p.m. - 5 a.m.)    | 0.82***  | 0.04       | 1.02***  | 0.05       |
|                | Battery                    | 0.02***  | 0.00       | 0.02***  | 0.00       |
| Nest 1         | ASC                        | -0.67*** | 0.05       | -3.53*** | 0.15       |
| Dockless       | Distance<sup>1</sup>       | -0.10*** | 0.03       | 1.77***  | 0.11       |
| E-Scooter      | Price                      | -0.28*** | 0.01       | -0.62*** | 0.02       |
| Provider #2    | Vehicle density            | 0.20***  | 0.00       | 0.24***  | 0.00       |
|                | Morning (6 a.m. - 9 a.m.)  | -0.25*** | 0.04       | -0.33*** | 0.04       |
|                | Night (9 p.m. - 5 a.m.)    | 0.46***  | 0.04       | 0.70***  | 0.05       |
|                | Battery                    | 0.00***  | 0.00       | 0.00***  | 0.00       |
|                | ASC                        | -2.66*** | 0.05       | -6.28*** | 0.16       |
| Dockless       | Distance<sup>1</sup>       | 0.85***  | 0.02       | 2.97***  | 0.11       |
| E-Bike         | Price                      | -0.12*** | 0.01       | -0.63*** | 0.03       |
|                | Vehicle density            | 0.16***  | 0.01       | 0.23***  | 0.02       |
|                | Elevation (gain)           | 0.02***  | 0.00       | 0.04***  | 0.00       |
|                | Battery                    | 0.00*    | 0.00       | 0.00     | 0.00       |
| Nest 2         | ASC                        | -0.42*** | 0.02       | -0.50*** | 0.06       |
| Docked         | Distance<sup>1</sup>       | 1.19***  | 0.03       | 6.81***  | 0.22       |
| Bike           | Vehicle density            | 0.03***  | 0.00       | 0.05***  | 0.00       |
|                | Elevation (gain)           | -0.02*** | 0.00       | -0.05*** | 0.00       |
|                | Morning (6 a.m. - 9 a.m.)  | 0.29***  | 0.04       | 1.71***  | 0.12       |
|                | Night (9 p.m. - 5 a.m.)    | -0.20*** | 0.05       | -2.10*** | 0.14       |
|                | Distance<sup>1</sup>       | 1.27***  | 0.03       | 6.91***  | 0.22       |
| Docked         | Vehicle density            | 0.04***  | 0.00       | 0.09***  | 0.00       |
| E-Bike         | Morning (6 a.m. - 9 a.m.)  | 0.28***  | 0.04       | 1.73***  | 0.11       |
|                | Night (9 p.m. - 5 a.m.)    | -0.14*** | 0.04       | -2.01*** | 0.12       |
|                | σ (nested error component) | 7.17***  | 0.19       |
|                | ρ2                         | 0.31      | 0.35       |
|                | AIC                        | 199'716   | 188'203    |
|                | Halton draws               | 200       |            |
|                | n                          | 139'559   | 139'559    |

***: p < 0.01, **: p < 0.05, *: p < 0.1
1 Estimate together for parsimony
2 log-transformed
Table 3 displays the results for both models. All coefficients except for the battery charge for docked e-bikes are highly significant and show the expected signs. Both models confirm our expectations from the bivariate analyses (the most important ones are reiterated here) yet reveal their relative influence. Micromobility mode choice is most strongly and significantly influenced by distance (positively for (e-)bikes and negatively for e-scooters). The morning peak strongly and positively influences mode choice for docked micromobility (e-bikes and bikes) and 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). This suggests that docked (e-)bikes are preferred for the commute while dockless e-scooters are preferred for other trips. Dockless e-scooter providers exhibit the highest utility gains from increasing vehicle densities. Elevation has a negative effect for docked bikes, which is intuitive as cycling up-hill takes time and energy; and has a positive effect for dockless e-bikes. Finally, increasing the price has the expected negative effect on mode choice, while the relative impact of battery charge is negligible.

The marginal probability effects (Hensher et al., 2015) for the NECLM model (Table 4) further illustrate some of the most important commercial trade-offs. For example, increasing the price of dockless e-scooter provider #1 by 1% will decrease its choice probability -0.94 percentage points. Dockless e-scooter provider #2 gains most from such a price increase (+0.53 percentage points) as would be expected, but some substitution also appears to take place between the other modes. In general, dockless e-scooter usage appears to be more sensitive to price changes than dockless e-bike use. Increasing vehicle density increases choice probability for all modes. However, the effect is highest for dockless e-scooter providers (+0.46 and +0.56 percentage points). Again, it becomes visible that both dockless e-scooter providers mostly compete against each other (i.e., if vehicle density increases for one, the other loses most choice probability in comparison to other modes).

### Table 4
Selected marginal probability effects for the NECLM model.

| Independent variables | Dockless E-Scooter #1 | Dockless E-Scooter #2 | Dockless E-Bike | Docked E-Bike | Docked Bike |
|-----------------------|-----------------------|-----------------------|-----------------|---------------|-------------|
| Price [CHF]           |                       |                       |                 |               |             |
| Dockless E-Scooter #1 | -0.94                 | 0.53                  | 0.18            | 0.15          | 0.08        |
| Dockless E-Scooter #2 | 0.84                  | -1.55                 | 0.33            | 0.25          | 0.13        |
| Dockless E-Bike       | 0.14                  | 0.15                  | -0.41           | 0.09          | 0.03        |
| Vehicle density [# in 2 min walking dist] |                       |                       |                 |               |             |
| Dockless E-Scooter #1 | 0.46                  | -0.26                 | -0.07           | -0.09         | -0.04       |
| Dockless E-Scooter #2 | -0.33                 | 0.56                  | -0.10           | -0.09         | -0.05       |
| Dockless E-Bike       | -0.04                 | -0.05                 | 0.11            | -0.02         | -0.01       |
| Docked E-Bike         | -0.06                 | -0.06                 | -0.04           | 0.25          | -0.09       |
| Docked Bike           | -0.02                 | -0.02                 | -0.01           | -0.09         | 0.13        |

### 6. Discussion

Our analyses reveal that users prefer docked (e-)bikes during peak hours and dockless e-scooters during off-peak hours. This indicates that docked (e-)bikes are preferred for the commute and thus may play an important role in reducing car traffic in peak hours. In contrast, dockless e-scooters are not preferred for such trips in Zurich. A possible reason for these preferences is that docked (e-)bikes have higher spatiotemporal vehicle availability and higher reliability of availability. Therefore, station-based operating models can better support habitual travel patterns compared to the dockless operating models.
This finding confirms results from previous studies that docked bikesharing systems are often used for commuting purposes (Bordagaray et al., 2016; Lathia et al., 2012; McKenzie, 2019; Zhao et al., 2015) and that the integration of bikesharing stations with public transport can increase the number of multimodal trips (Bordagaray et al., 2016; DeMaio, 2009; Martens, 2004; Martens, 2007; Rietveld, 2000a; Rietveld, 2000b). City regulators and vehicle providers could leverage and extend this concept by introducing multimodal "mobility hubs" near frequently used public transport stations and major employment centres where dockless modes could be stationed and charged to better support multimodal commutes including dockless modes. Docking stations could thus be a valuable addition to currently dockless e-scooter networks, breaking the seemingly dominant "either or" pattern of vehicle provision.

The physical integration of micromobility with public transport may, however, not be enough to foster intermodality and offer a truly attractive alternative to the private car. The literature on Mobility as a Service (MaaS) also explores the virtual integration of emerging transport modes with public transport through the integration of customer interfaces (apps) to enable intermodal trip-planning, booking and payment (Hensher et al., 2020a). The impact of MaaS on transport behaviour is still an open question and is currently investigated in three large trials in Australia, Germany and Switzerland. This research on micromobility mode choice, and particular the marginal effects of prices, could inform the size of incentives necessary to nudge customers of MaaS bundles towards more sustainable modes.

This paper further contributes to our understanding of the interactions between supply-side operational practices and customer demand. Two examples are the impact of vehicle density and the impact of battery charge on choice probability. Our results show that vehicle density has a particularly strong impact on the choice of dockless e-bikes and e-scooters, with more available vehicles yielding more bookings. However, marginal utility gains are decreasing up to a level of indifference, where more vehicles on the road do not increase choice probability any further (cf. Figure 4). We term this fundamental relationship the "plateau effect" for micromobility fleet densities. While further studies are needed to understand this effect in more detail, first evidence suggests that this effect also exists at the city-level (Krauss et al., 2020). Vehicle operators can start using this knowledge to optimise their relocating practices, for example by balancing marginal cost and utility for a better distribution of vehicles in the network. Policymakers can also use this evidence to define maximum numbers of e-scooters that are simultaneously allowed in certain areas of the city to prevent unnecessary blockage of public space.

7. Conclusions

This is the first study that comprehensively analyses usage, competition and mode choice for four different micromobility modes (dockless e-scooters, dockless e-bikes, docked e-bikes and docked bikes) at a high spatiotemporal resolution. We develop a generally applicable methodology to enable these analyses using only widely accessible vehicle location data, and estimate the first comprehensive mode choice models using the largest and densest empirical shared micromobility dataset to-date.

Our results suggest that mode choice is nested and dominated by distance and time of day. Docked modes are preferred for commuting. Hence, docking infrastructure could be vital for bolstering micromobility as an attractive alternative to private cars to tackle urban congestion during rush hours.

---

4 Three large-scale MaaS trials are currently on-going: Tripi in Australia, swa Augsburg in Germany and SBB in Switzerland. For first results, see Hensher et al. (2020b), Hensher et al. (2020c) and Reck et al. (2020c).

5 For an overview on MaaS bundle design, see Reck et al. (2020b).
Furthermore, our results reveal a fundamental relationship between fleet density and usage. A "plateau effect" is observed with decreasing marginal utility gains for increasing fleet densities. City authorities and service providers can leverage this quantitative relationship to develop suitable micromobility regulation and optimise their fleet deployment, respectively.

This study has some limitations that call for future work. First, the data used in this study is limited to only one city. However, our methodology is generally applicable to any city worldwide as the data used is widely accessible through a variety of data collection methods such as scraping openly accessible provider APIs. Therefore, similar analyses could be conducted in any other city to verify the external validity of our work. Second, our analysis focuses on the impact of provider-level and trip-level attributes on micromobility mode choice. This could be extended by including more modes (e.g., public transport and walking), user-specific attributes (e.g., sociodemographics, mobility tool ownership, micromobility service membership), and destination-specific attributes (e.g., public transport availability, type of destination). Third, transport network simulation is needed to fully understand the impact of micromobility on urban mobility and its sustainability. Our results on mode choice and underlying user preferences build the foundation for integrating micromobility in transport network simulations.

As the variety, availability and use of micromobility modes grow rapidly worldwide, the questions addressed in this study are likely to grow in relevance. This study provides first insights that help evaluate the impact of micromobility at system-level and its potential to substitute private cars, alleviate road congestion during rush hours, and reduce the footprint of urban transport. Using this evidence, city authorities can develop suitable regulation on critical issues such as vehicle licensing and parking space allocation, and plan transport infrastructure to support its sustainable use in conjunction with other modes. Service providers can evaluate their competitive positions and further optimise their operations.

Acknowledgements

The authors are very thankful to Roll2Go AG and Lukas Ballo for providing the main data used for our analysis and to Basil Schmid for providing useful comments on the modelling strategy.

References

Bachand-Marleau, J., B.H.Y. Lee, and A.M. El-Geneidy (2012) Better Understanding of Factors Influencing Likelihood of Using Shared Bicycle Systems and Frequency of Use. Transportation Research Record: Journal of the Transportation Research Board, 2314, 66-71.

Bai, S., and J. Jiao (2020) Dockless E-scooter usage patterns and urban built Environments: A comparison study of Austin, TX, and Minneapolis, MN. Travel Behaviour and Society, 20, 264-272.

Bordagaray, M., L. dell' Olio, A. Fonzone, and Á. Ibeas (2016) Capturing the conditions that introduce systematic variation in bike-sharing travel behavior using data mining techniques. Transportation Research Part C: Emerging Technologies, 71, 231-248.

Campbell, K.B., and C. Brakewood (2017) Sharing riders: How bikesharing impacts bus ridership in New York City. Transportation Research Part A: Policy and Practice, 100, 264-282.
Campbell, A.A., C.R. Cherry, M.S. Ryerson, and X. Yang (2016) Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. *Transportation Research Part C: Emerging Technologies, 67*, 399-414.

Caspi, O., M.J. Smart, and R.B. Noland (2020) Spatial Associations in Dockless Shared e-Scooter Usage. Paper presented at the *99th Annual Meeting of the Transportation Research Board*, Washington, January.

DeMaio, P. (2009) Bike-sharing: History, impacts, models of provision, and future. *Journal of Public Transportation, 12* (4) 41-56.

Du, Y., F. Deng, and F. Liao (2019) A model framework for discovering the spatio-temporal usage patterns of public free-floating bike-sharing system. *Transportation Research Part C: Emerging Technologies, 103*, 39-55.

Eccarius, T., and C-C. Lu (2020) Adoption intentions for micro-mobility - Insights from electric scooter sharing in Taiwan. *Transportation Research Part D: Transport and Environment, 84*, 102327.

Espinoza, W., M. Howard, J. Lane, and P. van Hentenryck (2020) Shared E-Scooters: Business, Pleasure, or Transit. Paper presented at the *99th Annual Meeting of the Transportation Research Board*, Washington, January.

Fishman, E., S. Washington, and N. Haworth (2013) Bike Share: A Synthesis of the Literature. *Transport Reviews, 33* (2) 148-165.

Fishman, E., S. Washington, and N. Haworth (2014) Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia. *Transportation Research Part D: Transport and Environment, 31*, 13-20.

Guidon, S., H. Becker, H. Dediu, and K.W. Axhausen (2019) Electric bicycle-sharing: a new competitor in the urban transportation market? An empirical analysis of transaction data. *Transportation Research Record: Journal of the Transportation Research Board, 2673* (4) 15-26.

Guidon, S., D.J. Reck, and K.W. Axhausen (2020) Expanding a(n) (electric) bicycle-sharing system to a new city: Prediction of demand with spatial regression and random forests. *Journal of Transport Geography, 84*, 102692.

Hawa, L., B. Cui, L. Sun, and A.M. El-Geneidy (2020) Scoot over: Determinants of shared electric scooter use in Washington D.C. Paper presented at the *99th Annual Meeting of the Transportation Research Board*, Washington, January.

He, Y., Z. Song, Z. Liu, and N.N. Sze (2019) Factors Influencing Electric Bike Share Ridership: Analysis of Park City, Utah. *Transportation Research Record: Journal of the Transportation Research Board, 2673*, 12-22.

Hensher, D.A., J.M. Rose, and W.H. Greene (2015) *Applied choice analysis*. Cambridge University Press, Cambridge, UK.
Hensher, D.A., C. Mulley, C.Q. Ho, J. Nelson, G. Smith, and Y.Z. Wong (2020a) *Understanding Mobility as a Service (MaaS) - Past, Present and Future*. Elsevier, Amsterdam.

Hensher, D.A., C.Q. Ho, D.J. Reck, G. Smith, Y.Z. Wong, S. Lormier, and I. Lu (2020b) The Sydney mobility as a service (MaaS) trial: Design, implementation and lessons. ITLS, The University of Sydney, Sydney, in progress.

Hensher, D.A., C.Q. Ho, and D.J. Reck (2020c) Mobility as a Service and private car use: evidence from the Sydney MaaS trial. Submitted to *Transportation Research Part A: Policy and Practice* on 11 May 2020.

Krauss, K., D. Goeddeke, and T. Gnann (2020) What drives the usage of shared transport services? Paper presented at the *20th Swiss Transport Research Conference*, Ascona, May.

Lathia, N., S. Ahmed, and L. Capra (2012) Measuring the impact of opening the London shared bicycle scheme to casual users. *Transportation Research Part C: Emerging Technologies*, 22, 88-102.

Lazarus, J., J.C. Pourquier, F. Feng, H. Hammel, S. Shaheen (2020) Micromobility evolution and expansion: Understanding how docked and dockless bikesharing models complement and compete - A case study of San Francisco. *Journal of Transport Geography*, 84, 102620.

MacArthur, J., J. Dill, and M. Person (2014) E-bikes in North America: results of an online survey. *Transportation Research Record: Journal of the Transportation Research Board*, 2468, 123-130.

Martens, K. (2004) The bicycle as a feederling mode: experiences from three European countries. *Transportation Research Part D: Transport and Environment*, 9 (4) 281-294.

Martens, K. (2007) Promoting bike-and-ride: The Dutch experience. *Transportation Research Part A: Policy and Practice*, 41 (4) 326-338.

Mathew, J.K., M. Liu, S. Seeder, and H. Li, and D.M. Bullock (2019) Analysis of E-Scooter trips and their temporal usage patterns. Institute of Transportation Engineers, *ITE Journal*, 89 (6) 44-49.

McFadden, D. (1974) Conditional logit analysis of qualitative choice behaviour. In P. Zarembka (Ed.) *Frontiers in Econometrics*, 105-142, Academic Press, New York.

McFadden, D. (1979) Quantitative Methods for Analysing Travel Behavior of Individuals. In D.A. Hensher and P. Stopher (Eds.) *Behavioral Travel Modeling*, 279-318, Croom Helm, London.

McKenzie, G. (2019) Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. *Journal of Transport Geography*, 78, 19-28.

Molloy, J., F. Becker, B. Schmid, and K.W. Axhausen (2019) mixl: An open-source R package for estimating complex choice models on large datasets. Paper presented at the *19th Swiss Transport Research Conference*, Ascona, May.

Murphy, E., and J. Usher (2015) The role of bicycle-sharing in the city: Analysis of the Irish experience. *International Journal of Sustainable Transportation*, 9 (2) 116-125.
Noland, R.B. (2019) Trip patterns and revenue of shared e-scooters in Louisville, Kentucky. 
*Transport Findings, 2019, April.*

Noland, R.B. (2020) Scootin' in the Rain: Does Weather affect Micro-mobility? *Working Paper, Alan M. Voorhees Transportation Center, Edward J. Bloustein School of Planning and Public Policy,* Rutgers University, New Brunswick, NJ, January.

Noland, R.B., M.J. Smart, and Z. Guo (2016) Bikeshare trip generation in New York City. 
*Transportation Research Part A: Policy and Practice, 94,* 164-181.

Reck, D.J., S. Guidon, and Kay W. Axhausen (2020a) Modelling shared e-scooters: A spatial regression approach. Paper presented at the *99th Annual Meeting of the Transportation Research Board,* Washington, January.

Reck, D.J., D.A. Hensher, and C.Q. Ho (2020b) MaaS Bundle Design. Submitted to *Transportation Research Part A: Policy and Practice* on 10 February 2020 (first submission) and 12 May 2020 (revised submission).

Reck, D.J., K.W. Axhausen, D.A. Hensher, Q.C. and Ho (2020c) Learning from the MaaS experience in Augsburg, Germany. *IVT Working Paper Series, 1469,* ETH Zurich, Zurich.

Ricci, M. (2015) Bike sharing: A review of evidence on impacts and processes of implementation and operation. *Research in Transportation Business & Management,* 15, 28-38.

Rietveld, P. (2000a) Non-motorised modes in transport systems: a multimodal chain perspective for The Netherlands. *Transportation Research Part D: Transport and Environment,* 5 (1) 31-36.

Rietveld, P. (2000b) The accessibility of railway stations: the role of the bicycle in The Netherlands. *Transportation Research Part D: Transport and Environment,* 5 (1) 71-75.

Shaheen, S.A., S. Guzman, and H. Zhang (2010) Bikesharing in Europe, the Americas, and Asia: past, present, and future. *Transportation Research Record: Journal of the Transportation Research Board,* 2143, 159-167.

Shaheen, S., H. Zhang, E. Martin, and S. Guzman (2011) Hangzhou public bicycle: Understanding early adoption and behavioural response to bike sharing in Hangzhou, China. Paper presented at the *90th Annual Meeting of the Transportation Research Board,* Washington, January.

Shen, Y., X. Zhang and J. Zhao (2018) Understanding the usage of dockless bike sharing in Singapore. *International Journal of Sustainable Transportation,* 12 (9) 686-700.

Walker, J.L., M. Ben-Akiva and D. Bolduc (2007) Identification of parameters in normal error component logit-mixture (NECLM) models. *Journal of Applied Econometrics,* 22 (6) 1095-1125.

Younes, H., Z. Zou, J. Wu, and G. Baiocchi (2020) Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, D.C., *Transportation Research Part A: Policy and Practice,* 134, 308–320.
Zhao, J., J. Wang, and W. Deng (2015) Exploring bikesharing travel time and trip chain by gender and
day of the week. *Transportation Research Part C: Emerging Technologies*, **58**, 251-264.

Zhu, R., X. Zhang, D. Kondor, P. Santi, and C. Ratti (2020) Understanding spatio-temporal
heterogeneity of bike-sharing and scooter-sharing mobility. *Computers, Environment and Urban
Systems*, **81**, 101483.

Zuniga-Garcia, N., and R. Machemehl (2020) Dockless Electric Scooters and Transit Use in an
Urban/University Environment. Paper presented at the *99th Annual Meeting of the Transportation
Research Board*, Washington, January.