

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

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Explaining Shared Micromobility Usage, Competition and Mode Choice by Modelling Empirical Data from Zurich, Switzerland

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1 Motivation

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 single modes, only few comparative studies of two modes exist and none so far have analysed competition or mode choice at a high spatio-temporal resolution for more than two modes.

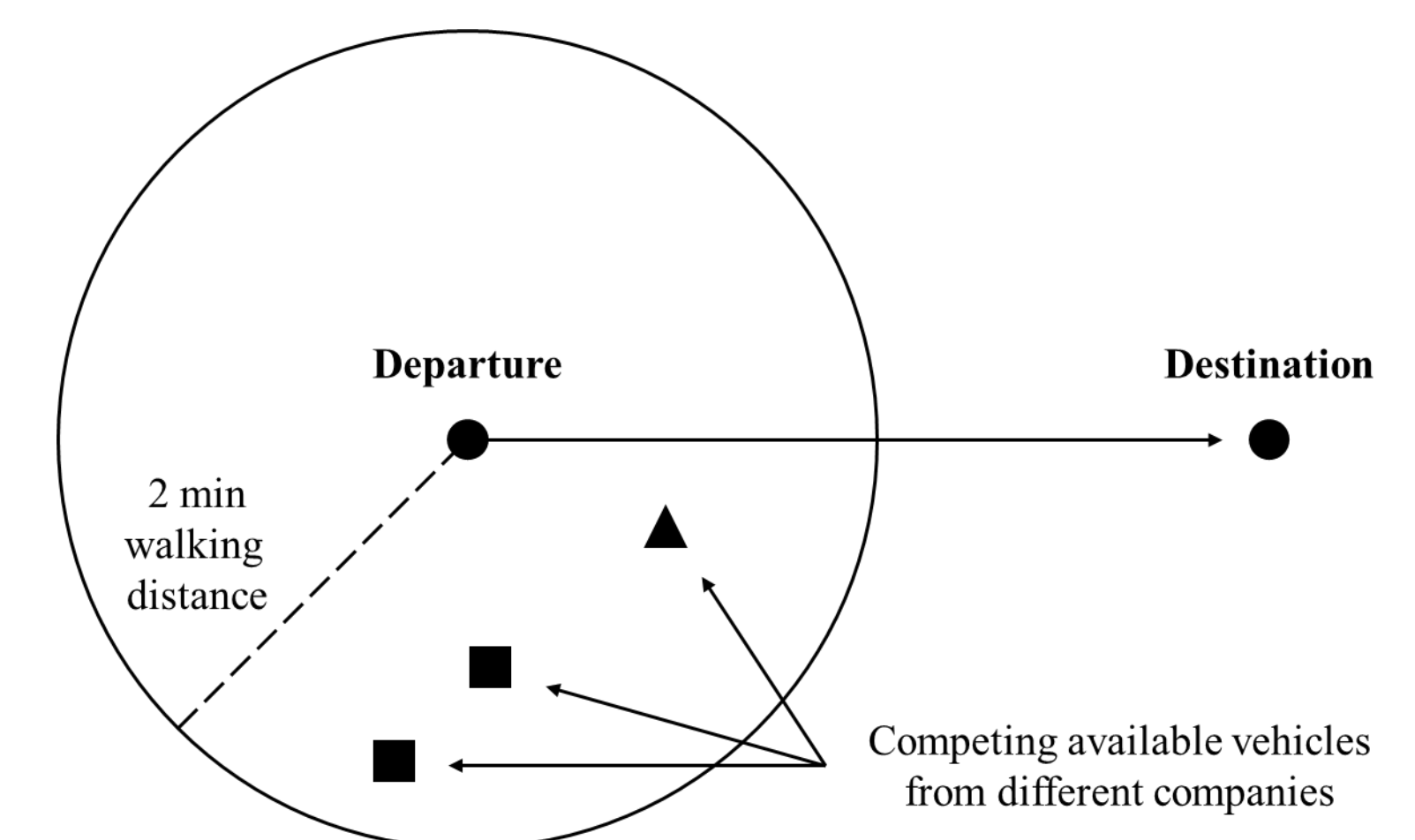
Why is it critical to fill this knowledge gap? First, understanding mode choice is the quintessential first step towards including micromobility modes in transport network simulations to analyse their impact at the system level. Second, it clarifies their potential to substitute car trips, alleviate roads during the commute and reduce the footprint of urban transport and thus enables evidence-based policymaking. Third, it provides insights into trade-offs and marginal effects, enabling existing providers to further optimize their operations and prospective providers to evaluate their competitive positions.

2 Data

We collect data in Zurich, Switzerland. Our raw dataset consists of vehicle location data. Between 1 Jan. and 29 Feb. 2020, we queried 4 micromobility companies' APIs every ~60s for all available vehicles, collecting over 169M observations. Each observation contains information on a vehicle's location (GPS lon/lat), an ID, a timestamp and the battery charge (if applicable). Each vehicle appears as a sequence of observations over time when it is available to be booked. Conversely, we define a disappearance of a previously observed vehicle as a trip. We filter out falsely identified trips due to GPS inaccuracies and operator actions (for details, see paper).

In sum, we obtain a total of 168'895 trips during the two months of analysis (~2'800 / day). We next identify choice sets from vehicle location data and vehicle trip data. 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 (Fig. 1). Each choice set for a trip is thus composed of 1 to 5 available modes / companies and several attributes that vary by mode and trip. These include the number of available vehicles within 2 min walking distance from the departure location ("vehicle density"), the battery charge, prices, the chosen mode, the time of day, the elevation difference between origin and destination, and the distance.

FIGURE 1 Spatiotemporal window to identify choice sets of competing micromobility vehicles.



3 Method

We explore bivariate relationships between the attributes and the choice probabilities for each company and mode (Fig. 2) and we estimate choice models to explore their joint effect on mode choice.

As choice behaviour could be nested (some users might only be member of certain types of shared micromobility schemes), we also estimate a model with nested error terms (normal error component logit-mixture model, NECLM). 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". Please refer to the full paper for utility function specifications and full estimation results.

4 Results

The NECLM model (Table 1) has an excellent fit with a McFadden pseudo R^2 of 0.35. Our results suggest that mode choice is nested (dockless and docked) 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.

FIGURE 2 Bivariate relationships (selection) of attributes and choice probability (smoothed lines).

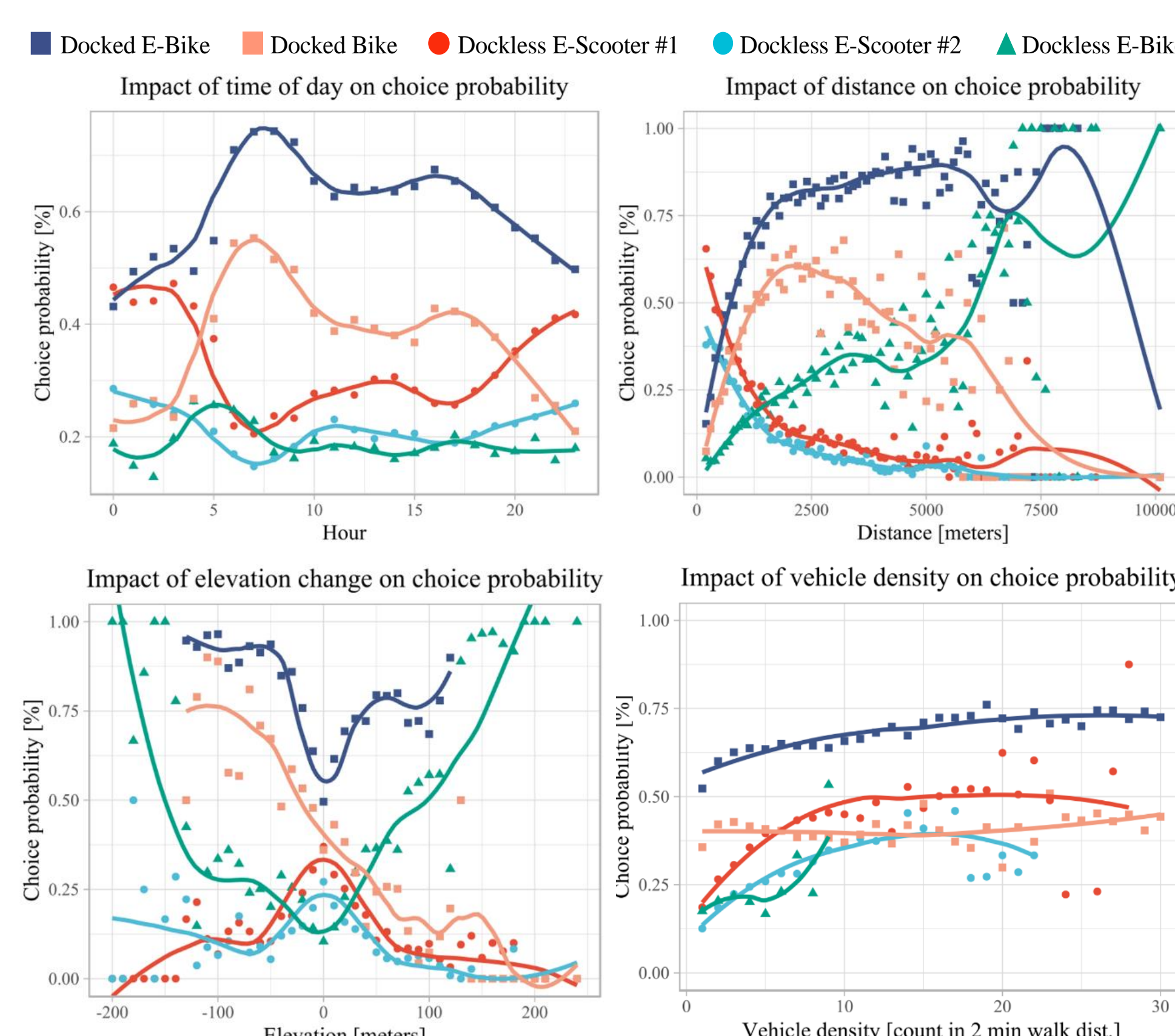


TABLE 1 Estimation results for NECLM model (full table see publication).

Mode / Company	Parameter	EST	SE
Nest 1	ASC	-5.01***	0.16
	Distance ¹	1.77***	0.11
	Price	-0.46***	0.02
	Vehicle density	0.21***	0.00
	Morning (6 a.m. - 9 a.m.)	-0.35***	0.05
	Night (9 p.m. - 5 a.m.)	1.02***	0.05
	Battery	0.02***	0.00
...	...		
Nest 2	ASC	-0.50***	0.06
	Distance ²	6.81***	0.22
	Vehicle density	0.05***	0.00
	Elevation (gain)	-0.05***	0.00
	Morning (6 a.m. - 9 a.m.)	1.71***	0.12
	Night (9 p.m. - 5 a.m.)	-2.10***	0.14
...	...		
	σ (nested error component)	7.17***	0.19
	ρ^2		0.35
	n		139'559